Assessment of the Influence of Medicare Graduate Medical Education Payments on Hospital Sponsorship of Residency Training

By

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ABSTRACT

KATHLEEN DALTON. Assessment of the Influence of Medicare Graduate Medical Education Payments on Hospital Sponsorship of Residency Training
(Under the direction of Kerry E. Kilpatrick, M.B.A., Ph.D.)

Federal policy assumes that Medicare payments influenced growth of residency sponsorship under PPS, and that reduction in GME payments can encourage reduction or slow the growth of sponsorship. This study assesses the role of reimbursement incentives in hospital residency sponsorship decisions. Variation across hospitals in marginal per-resident GME payment is exploited in order to investigate the strength of financial incentives, within a model of hospital demand for residency training that incorporates service delivery needs, mission and competition.

Panel data are analyzed from cost reports on all short-term hospitals for the first 12 years under PPS. Medicare data are merged with data from AHA, ARF and NIH. To investigate effects by type of resident and length of training, resident FTE counts are supplemented by specialty-specific data from HCFA's IRIS files. Change in resident FTEs is analyzed as a function of lagged real GME payments/resident, changes in hospital services, indigent care, research and other hospital characteristics. Interaction terms test differences in effect by academic affiliation and time. Control for contemporaneous correlation is achieved using GEE. Among non-teaching hospitals, logit assesses the 12-year probability of converting to teaching status as a function of

potential GME payments, after controlling for hospital and community covariates as of the beginning of the period.

No significant main or interacted effects are identified between potential reimbursement gains and likelihood of conversion to teaching status. Among existing teaching hospitals, Medicare payment incentives are found to be moderately associated with training expansion, in later periods and among academic programs only. Measurement error in IRIS data prevented the model from controlling for effects of extended training time. The strongest predictors of expansion were academic and research missions, and service delivery. The model associates a 20% change in GME payments with a 10% change in annual increases in residents; in comparison, a 20% change in critical care capacity is associated with a 56% change in the increase in residents.

This study provides no strong evidence that GME decisions were governed by short-term reimbursement maximization strategies under PPS. More explicit regulatory intervention may be required to implement policy goals for reduced GME sponsorship.

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LIST OF ABBREVIATIONS

AAMC	Association of American Medical Colleges
ACGME	Accreditation Council for Graduate Medical Education
ACPR	Average Cost Per Resident
AHA	American Hospital Association
AMA	American Medical Association
ARF	Area Resource Files
BBA	Balanced Budget Act of 1997
CBO	Congressional Budget Office
CEO	Chief Executive Officer
CMI	Case Mix Index
COGME	Council On Graduate Medical Education
DME	Direct Medical Education
DRG	Diagnosis-Related Groups
DSH	Disproportionate Share
FTE	Full Time Equivalent
GAO	Government Accounting Office
GME	Graduate Medical Education
GMENAC	Graduate Medical Education National Advisory Council
HCFA	Health Care Financing Administration
HCRIS	Hospital Cost Report Information System
IME	Indirect Medical Education

IMG	International Medical Graduate
IOM	Institute of Medicine
IRB	Intern & Resident Bed Ratio
IRIS	Intern & Resident Information System
MedPAC	Medicare Payment Advisory Commission
NHSC	National Health Service Corps
NIH	National Institute of Health
PPRC	Physician Payment Review Commission
PPS	Prospective Payment System
ProPAC	Prospective Payment Advisory Council
PSF	Provider Specific File
RRC	Residency review Committee
TEFRA	Tax Equity and Fiscal Responsibility Act of 1981
VA	Veterans Administration

1 Introduction

This dissertation investigates the relationship between Medicare payments for graduate medical education (GME) and the growth in post-graduate medical residency sponsorship across Medicare participating hospitals for a period spanning from 1984 to 1996. In 1981 the Graduate Medical Education National Advisory Committee concluded that the nation was already training a sufficient number of physicians for projected population needs and that it should stop expanding medical school capacity. Since that time undergraduate allopathic schools of medicine in the United States have stopped expanding their graduating class sizes. In this country it is the hospital-based postgraduate programs that are responsible for virtually all residency training leading to medical licensure and certification, however, and since 1981 the number of physicians in approved postgraduate training has increased by over 40% [1]. Some of this growth reflects longer training periods that are the results of increased medical specialization, but first-year training positions have also continued to grow by 1-2% per year. Hospitals are coming under increasing criticism for contributing to perceived over-production of physicians by filling new residency training slots with graduates of international medical schools, the majority of whom will remain in the U.S. to practice medicine.

Medicare's Prospective Payment System (PPS) is a system of federally administered hospital prices that became effective in 1984. PPS replaced retrospective cost-based reimbursement as a method for paying hospitals for inpatient services

delivered to Medicare beneficiaries. Under PPS, Medicare developed explicit mechanisms to pay additional amounts to hospitals that participate in GME activities. These GME payment formulas, which increase according to the absolute level and intensity of residency sponsorship, are frequently criticized for creating financial incentives for hospitals to expand residency programs beyond what would be reasonable or appropriate for educational and workforce planning needs. To date, however, no systematic empirical studies have been conducted to evaluate the influence of Medicare payments on hospitals' GME sponsorship.

Until 1998 the Medicare program made GME payments available to any teaching hospital for as many residents as the hospital chose to sponsor, provided that the training programs met their respective accreditation standards. The Balanced Budget Act of 1997 (BBA) eliminated this open-ended support. It placed an upper limit on the number of positions eligible for inclusion in the PPS teaching adjustment calculations, which effectively reduces the marginal reimbursement impact of expanding GME training programs to zero. The motivations for doing this were partially budget driven, with estimated savings from all GME payment-related changes as high as $5.6 billion over five years [2]. Provisions of the law also specifically address reduction in GME training as a federal workforce objective. A "Resident Reduction Incentive" plan sets up a separate incentive program to protect hospitals from short term Medicare losses that would normally result from reductions in sponsored residents, if the hospitals agree to make substantial cuts in their resident complement.

The GME payment provisions that were finally included in BBA were the culmination of a decade of intensive political debate and legislative compromise over the

appropriate role of government in influencing the size and composition of the physician workforce. After 1994, political support waned for any direct regulatory intervention that would impose external restrictions on residency training or licensure. Manipulation of Medicare reimbursement incentives remained as one of the few acceptable tools with which to exert federal influence over physician workforce decisions. The BBA provisions eliminated Medicare payment incentives for expanding hospital-based GME sponsorship, increased payment incentives for moving training out of hospitals and into certain ambulatory sites, and reduced potential financial barriers to substantive reductions in total GME sponsorship, all in the belief that payment incentives play a significant role in residency training decisions.

The extent to which the BBA will have an effect on the number of residents trained depends upon the importance of Medicare hospital payments to GME decision-making. In practice graduate medical education decisions are the product of joint negotiations among hospitals, their medical staffs, academic affiliates and professional accreditation boards. One purpose of this study is to gain a better understanding of the influence of financial incentives on the hospital's contribution to this process. Such knowledge may help policy makers to assess the effectiveness of Medicare payment rule changes as potential regulatory tools to affect hospitals' GME participation decisions and thus ultimately to influence physician supply.

There is substantial variation across hospitals in the size of Medicare GME payments and in the rate of increase in the number of residents sponsored. This variation can be exploited to identify the independent contribution of financial incentives to GME program growth after controlling for the effects of other factors expected to influence

hospital training decisions. To investigate the role of financial incentives, this study analyzes twelve years of Medicare cost report data, supplemented for the last seven years by a relatively new HCFA audit database known as the Intern and Resident Information System ("IRIS"). IRIS files document individual residents' rotations across approved teaching hospitals, according to how each teaching hospital claims them for GME reimbursement. IRIS data allow the tracking of Medicare GME payments by individual residents, aggregated to the levels of graduate year and specialty program, within hospitals and over time. Data on resident full time equivalents are merged with Medicare payment information from HCFA cost report files and with operating and academic characteristics derived from other HCFA files and AHA files. The study population consists of all short-term, acute care, non-federal hospitals receiving Medicare payments for years between 1984 and 1996. The period corresponds to the first twelve years of Prospective Payment System implementation (or PPS Years 1 - 12) [1]. IRIS data are available for more detailed analyses only after 1989 (PPS Year 6).

Only one in ten hospitals that receive Medicare GME payments is tied through ownership or control to a school of medicine. In the non-academic teaching hospitals, decisions regarding the type and intensity of residency training remain primarily in the hands of hospital management. In both academic and non-academic settings, GME payments would be less likely to serve as incentives to expand teaching commitments if the incremental reimbursement that was received reflected the incremental costs of expansion. The direct costs of adding a new resident are straightforward to measure and

[1] "PPS Year" covers a period defined by the date on which a provider's fiscal year begins. For example, PPS 11 includes hospitals with fiscal years beginning on or after October 1, 1993 and before October 1, 1994. PPS Year 11 is often identified with the federal fiscal year ending September 30, 1994, but cost

compare to payments. A considerable body of literature also exists, however, documenting what are often called the "indirect costs" of medical education. The empirical work has established an independent cross-sectional association between teaching intensity and average operating costs per discharge, and has served as the basis for incremental payments made under PPS, for care delivered in teaching settings. In previous work, I have re-estimated these earlier cost models using pooled cross-sectional data on Medicare operating costs over a seven-year period. These investigations were unable to identify a similar association between changes in teaching intensity and operating costs within individual hospitals, over time. This finding established a basis for asking the central dissertation question, "to what extent did reimbursement maximization strategy drive hospital residency training decisions?"

Using year-to-year changes in resident FTEs as the outcome variable, a model is developed that assesses the influence of Medicare GME payments on changes in residency sponsorship, after controlling for increases in hospital demand for resident labor and for other covariates. The main study period covers PPS years 1 through 12. For the subset of years when IRIS data are available, the model is also tested using changes in both total residents and first-year residents as the outcome variable. Secondary models are developed from the IRIS data that are restricted to residency program growth within groups of specialties, and to international as compared to domestic medical graduates.

The potential for reimbursement gain may also have influenced non-teaching hospitals to begin participating in residency training, whether by affiliation with existing

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reports from this period could include hospitals with 12-month period-end dates between September 30, 1994 and August 31, 1995.

teaching hospitals or by sponsorship of newly accredited programs. This possibility is investigated by following the cohort of all hospitals that did not participate in GME at the beginning of the Prospective Payment System implementation (1984-1985). Potential incremental GME payments per new resident (which can vary across hospitals according to the size and diagnostic mix of their Medicare caseloads) are computed for the study hospitals, which are followed over a twelve year period to identify those that become teaching hospitals at a later time. A probability model is constructed to investigate the association between potential reimbursement gains and the likelihood of converting from non-teaching to teaching status during this period.

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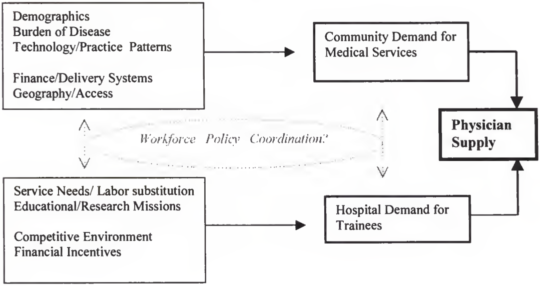
2. MEDPAC. Report to Congress: Medicare Payment Policy, Volume II (Chapter 3). Washington, D.C.: Medicare Payment Advisory Commission; 1998 Mar.

2 Background – Workforce Issues

2.1 Physician Supply

The Physician Payment Review Commission (PPRC) has described physician supply in the U.S. as responding to two separate markets [3]. One market derives from the community's demand for medical services, the other from hospitals' demand for trainees. The absence of a coordinated national health workforce policy in the United States allows these two markets to function independently. Factors that affect the demand for medical services do not necessarily affect hospital demand for resident labor at the same time, or even in the same direction. In the absence of regulatory intervention, the two markets are capable of reflecting conflicting goals.

Figure 2.1 Two-Market Model of Physician Supply



As illustrated in Figure 2.1, demand for medical services is traditionally viewed as a function of demographics and the burden of disease, modified by advances in medical technology, trends in the organization and financing of the delivery system, the environment, and patient and community socioeconomic status. Hospital demand for residents, by contrast, responds to few of these factors.

In the United States virtually all post-graduate training is under the control of hospitals. Only 10% of teaching hospitals are linked through ownership or control (and therefore mission) with the schools of medicine whose goals might be expected to reflect national trends in demand for medical services. Within hospitals, residents substitute heavily for technical staff as well as professional medical providers. They function as inexpensive physicians in medically under-served neighborhoods where outpatient departments provide substantial portions of the community's primary care. Demand for resident labor is expected to correlate most strongly with measures of hospital service delivery. In teaching settings, institutional decisions to add subspecialties may be driven not only by hospital service needs, but also by the need to maintain academic reputations and to support research and teaching infrastructure. Among community hospitals, residency training may represent a form of non-price competition, attracting admitting physicians by offering additional professional status as clinical faculty and providing relief from after-hours care. Finally, because Medicare (and sometimes Medicaid) payments for patient services increase with the number of residents on site, hospital decisions to expand training sponsorship may be part of their reimbursement maximization strategy.

Since 1981, US allopathic schools of medicine have voluntarily held the number of their graduates to about 17,000 per year, in recognition that the nation was approaching a balance in physician need and supply. From 1981 to 1996, however, hospitals increased total the number of residency training slots offered by 2%-3% per year; in 1995 there were over 23,000 new first-year residency positions available at US hospitals (including military and veterans' facilities) [4; 5]. Thus there has been a discontinuity between the undergraduate medical production objectives of the 125 allopathic medical schools and the post-graduate production decisions of approximately 1,200 teaching hospitals. Market signals that might reflect a surplus of practicing physicians in the community — such as reduced job opportunities or flattening incomes — do not appear to be affecting hospital demand for resident labor. In theory market signals should affect the training decisions of U.S. medical graduates, which in turn should affect the hospital's supply of resident applicants [6; 7]. In the subspecialties where this may have occurred in recent years, however, there has been a ready supply of international medical graduates available to fill training slots [8]. While some of the subspecialties have instituted small reductions in their first-year training slots since 1994, expansion in relatively new specialties, such as emergency medicine and rehabilitation, has offset these changes [9].

Over the past thirty years, trends in supply and demand for physician services have been studied extensively by government agencies and public policy groups. The Graduate Medical Education National Advisory Committee (GMENAC) was created in 1976 and charged with advising the Secretary of Health & Human Services on the nation's future physician supply needs, following two decades of active federal support

for the expansion of undergraduate medical training. Their specialty-specific forecasting models became the prototypes for the Bureau of Health Professions models that are still used today. In 1986 the Council on Graduate Medical Education (COGME) succeeded GMENAC as the leading federal advisory body on workforce training needs, but several private foundations have also undertaken workforce planning and policy studies. These include the Pew Memorial Trust, the Josiah H. Macy Foundation and the Robert Wood Johnson Foundation.

Bureau of Health Professions data, summarized in Table 2.1 below, show that the total active physician/population ratio grew 66% from 1950 to 1990. By 1990 the ratio had already exceeded the figure of 220/100,000 which GMENAC had projected for the year 2000.

Table 2.1: U.S. Physician Supply, 1950 – 2000

	1950	1960	1970	1980	1990	(projected) 2000
Total Active Physicians (*)	219,900	259,400	323,800	453,200	601,200	731,900
% increase over previous decade		+ 18%	+ 25%	+ 42%	+33%	+ 22%
Active Physicians/100,000 pop (*)	142.2	141.6	155.8	195.9	236.9	260.7
% increase over previous decade		+ 10%	+ 10%	+ 26%	+ 21%	+ 10%
Patient Care Physicians (**)	172,400	203,400	238,700	344,900	456,100	570,800
% increase over previous decade		+ 18%	+ 17%	+ 44%	+ 32 %	+ 25%
Patient Care Physicians/100,000 pop	111.5	111.0	114.7	149.1	181.7	203.3
% increase over previous decade(**)		- 0% -	+ 3%	+ 30%	+ 22%	+12%

Sources: (*) Bureau of Health Professions projections. Adapted from Figure 2.1 in COGME 7th Report [10](**) Adapted from David Kindig [11]

Estimates of the supply of patient care physicians vary widely, according to how trainees and non-patient care time are counted [12; 13]. Estimates from 1992 indicated that 16% of active physicians were residents or fellows, 12% were engaged in teaching, research or administration, and the activities of another 10% could not be verified [11]. Estimates of demand for medical services also vary, according to the baseline assumptions used regarding the extent of health insurance coverage, the extent of managed care's influence over utilization patterns and the use of non-physician providers [14]. A consensus has developed that the U.S. has at least a sufficiency of physicians and is headed toward a significant surplus, although the timing and size of the surplus are subject to continuing debate due to the differences noted above. Overall physician needs projections from recent research range from 60 to 80 generalists and from 85 to 105 specialists per 100,000-population [15]. The two projections are not additive, since the generalist/specialist mix would affect the division of medical services and therefore the total physician need. With 56% of U.S. graduates matching to residency slots in generalist specialties [16] and nearly 30% of recent graduates indicating a preference for general practice careers [17], the total supply of generalists is expected to remain in balance with population needs even though certain urban/rural geographic mal-distributions may remain. The supply of specialists, however, is already well in excess of the most generous estimates of population-based needs. COGME projections expected the specialist ratio to reach 145/100,000 by the year 2000 [10]. The most recent figures from the Bureau of Health Professions estimate that the ratio of practicing, non-primary care physicians in 1998 is 117/100,000 excluding trainees, and 139/100,000 including trainees. [18]

A workforce policy statement issued jointly in December, 1997 by the Association of American Medical Colleges, the American Medical Association, The American Osteopathic Association and three other leading professional groups called for immediate reductions in the number of new physicians trained, particularly among international medical graduates. This document is a strong indicator of the breadth of the current consensus [19].

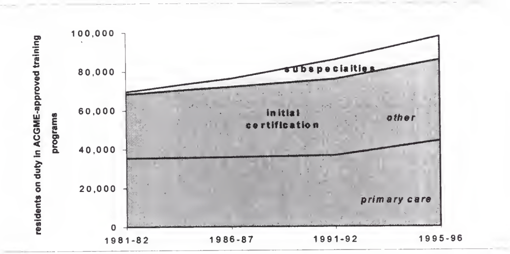
2.2 GME Sponsorship

The AMA conducts annual surveys of training programs to document graduate medical education trends, summarizing the results each year in JAMA. The number of residents in approved training positions in U.S. hospitals has increased from 70,000 in 1981 to over 98,000 in 1997 [4;5]. Not all of the new positions represent additional physician FTEs, since some of the growth reflects extended training time. Yet the number of first year positions has exceeded the number of domestic medical school graduates by approximately 40% throughout the 1990's. As shown in Figures 2.2 and 2.3, graduates of foreign schools therefore fill a moderately increasing proportion of total training slots. Of these, only 30% are expected to return to their countries of origin for practice [20]. Consequently, the majority of new training positions represent long term additions to the domestic physician workforce.

The teaching hospital's ability to expand physician training capacity is constrained only by the restrictions imposed by individual accreditation bodies of the medical and surgical specialty societies. Standards for expansion of accredited programs are more limiting in some specialty fields than others, but they are based primarily on

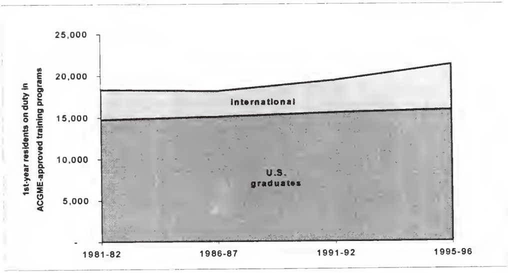
requirements to assure trainee exposure to an appropriate mix of clinical case material, under appropriate faculty supervision.

Figure 2.2 Growth in ACGME-sponsored residents, 1981 – 1996



Source: AMA analyses of graduate medical education, appearing in the annual medical education issues of JAMA. [4;5]

Figure 2.3 Growth in First Year ACGME-sponsored residents, 1989-1996



Source: AMA analyses of graduate medical education, appearing in the annual medical education issues of JAMA [4;5].

In general, surgical specialties have retained the tightest control over expansion in accredited programs. Some specialty societies have developed their own forecasting and demand models, the results of which may affect the level of influence which the societies exert at the national level, on expansion of their own training programs.

2.3 Federal Workforce Policy

From the 1950's through the 1970's federal and state governments took actively expansionist stances with regard to physician workforce policy. This was in response to perception of a growing physician shortage, particularly after Medicare legislation expanded medical care access for the elderly. Federal capitation funding (per medical student) and construction grants encouraged the expansion of medical school capacity, while special immigration status was allowed to encourage foreign-trained physicians to relocate in the U.S. By 1980 many of these policies (particularly the undergraduate funding incentives) were curtailed, in recognition of their success in addressing domestic physician supply issues [21].

Medicare's participation in the direct costs of medical education has always been restricted to funding the activities of post graduate trainees engaged in patient care, which can be interpreted principally as payment for value of services delivered. Under the PPS payment regulations effective after 1983, the mechanics of support for Medicare's share of stipend and supervisory costs were continued, with no particular federal role to influence the size or shape of the future workforce. By the mid-1980's, concern about a potential specialist surplus had grown sufficiently that Congress enacted changes in the Medicare payment formulas to reimburse hospitals only one-half as much for the later

years of training in certain surgical and sub-specialist trainees. The differences in total GME payments, however, were very slight.

Throughout the 1990's regulatory interventions intended to shape or limit GME training decisions were recommended by several private and government workforce policy groups. These include the Council on Graduate Medical Education (COGME) [10;22;23], the Pew Charitable Trust's Health Professions Commission [24;25], the PPRC Reports to Congress [3;6] and the Institute of Medicine [26]. Table 2.2 below, adapted from one by Oliver Fein [27], shows how widespread the attention has been to this issue throughout the decade.

Table 2.2 Approaches to Physician Workforce Reform
Adapted from Oliver Fein, "Funding Graduate Medical Education"

Organization	50/50 rule for % of primary care / specialty trainees	Reduction in total number of post graduate trainees	Reduction in total number of undergraduate trainees	Finance GME through central trust fund, from taxes on all 3rd-party payers
COGME	X	X		X
PPRC		X		X
ProPAC (*)	X			X
Pew Commission	X	X	X(adopted in '96)	X
RWJ Foundation	X			
Macy Foundation	X	X		X
AMA	X	X (adopted in '97)		X
AAMC	X	X (adopted in '97)		X
AAFP (**)	X	X		X
ABIM (***)	X	X		X
AOA (****)	X	X		

(*) Prospective Payment Assessment Commission (**) American Academy of Family Physicians
(***) American Board of Internal Medicine (****) American Osteopathic Association

Many of these recommendations made their way into proposed health reform legislation. Clinton's Health Security Act, for example, contained provisions for a general tax-supported medical education trust fund that would both centralize the financing of graduate medical education and create a regulatory body to determine the numbers and allocation of physician trainees. These provisions were almost identical to recommendations from the 1992 COGME report. Prior to the Health Security Act, health reform legislation proposed by Senator Mitchell and Rep. Gephardt contained similar proposals for GME reform. In 1992 Senator Rockefeller and Rep. Waxman sponsored legislation that would have mandated a reduction in the number of first-year residency slots receiving Medicare payments, from 24,000 to 19,000, over a period of five years [28]. Though none of these proposals became law, support grew for what is called the "110% -50/50 solution" which proposes to limit new first-year positions to no more than 110% of the number of U.S. medical school graduates, and divides such slots equally between primary care and other specialties. In 1993 the PPRC recommended that Congress should set limits on the number of funded physician trainees, with allocation decisions to be determined by the existing structure of accreditation bodies and their respective Residency Review Committees [29]. Recently COGME has made similar recommendations, but has focused on less centralized regulatory models in the form of state-level planning authorities or regional GME consortia [10;30]. The Pew Health Professions Commission recommended similar consolidation of authority in the hands of specialty accrediting bodies, but coupled this with financial penalties to hospitals failing to comply with the authorities' recommended training slot reductions [24;25].

Throughout the debate, much attention has been focused on the role of international medical graduates in allowing hospitals to meet their expanding demand for trainees [20;31-33]. Regulatory proposals varied in the extent to which IMGs or non-U.S. citizen graduates were singled out for restricted entry as a means of reducing total trainees. Proposals to limit the number of new training slots to 110% of the U.S. graduating class, for example, allowed the extra 10% in order to absorb the number of US citizens who trained in international schools. Although theoretically all IMGs could compete for the slots alongside domestic graduates, historically the National Resident Match Program appears to fill slots sequentially with domestic graduates first, then IMGs [8]. The vetoed Balanced Budget Act of 1996, by contrast, contained language that eliminated funding for any resident who was not a US citizen, regardless of what school he or she attended.

In spite of the growing policy-level consensus, legislation for medical education reform has met with little reliable political support [34]. Regulation restricting the number of new trainees and/or modifying their specialty mix requires some centralized method of trainee slot allocation among existing teaching institutions, for which a political consensus at the federal level has proven difficult to obtain. Support for overt regulatory control has weakened since the 1994 elections and to date the only national medical education reform proposals to become law are those limited to reducing Medicare's GME reimbursement formulas. Federal influence over residency training may, therefore, be limited in the near future to the manipulation of third-party patient care payment incentives.

The importance of Medicare GME payments to the operating margins of teaching hospitals has been well documented by agencies such as the Prospective Payment Assessment Commission [35] and the Association of Academic Medical Colleges [36]. There is little question that GME payment reduction can significantly threaten the financial stability of many teaching facilities, particularly those that are publicly owned. Which of these institutions is likely to respond to reduced funding by reducing its residency sponsorship, however, is a different and less researched question. There is little reason to expect uniform response. In academic medical centers where much of the growth in subspecialty training has occurred, hospital financial interests may play a smaller role in medical education decisions, because control over graduate teaching decisions is heavily influenced by medical school deans and clinical department chairs. Many inner-city hospitals are dependent on IMG residents to provide basic medical services to indigent populations. In these settings the cost of replacing residents with alternative professional providers may be so high that eliminating GME dollars without simultaneously imposing other regulatory restraints on hiring IMGs may have no effect, other than to increase the hospitals' needs for other public subsidies to replace diminished Medicare dollars. In the community affiliate programs where much of the expansion in Family Medicine training has taken place, reimbursement incentives may prove to be a stronger influence. If this is true, reducing GME payments could have unintended consequences for workforce policy goals with respect to specialty mix, because reimbursement incentives could preferentially reduce training at sites with less of a specialty emphasis.

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3 Background – The Role of Medicare

3.1 Teaching Hospitals

During Federal Fiscal Year 1994-1995, corresponding to PPS Year 12 [1], there were approximately 6,100 U.S. hospitals participating in the Medicare program excluding VA facilities. Of these, roughly 1,100 were specialty hospitals and 5,000 were short-term general care facilities. Fifteen percent of specialty and twenty-two percent of general hospitals participate in postgraduate medical training, but the intensity of teaching activity is highly variable. Teaching facilities are divided into those linked by ownership or control with medical schools ("academic health centers", or AHCs), community hospital-based accredited programs ("community programs"), and affiliates which receive residents on clinical rotations from other accredited programs ("community affiliates"). Community programs and affiliates are often divided into "major" and "minor" groups according to size and breadth of training activities. For this study, "major teaching" refers to facilities belonging to the Council of Teaching Hospitals (COTH) and can include both AHC and community-based programs. Teaching hospitals tend to be larger, located in larger communities and are rarely investor-owned. As is evident from Table 3.1, hospital size and level of patient care sophistication increase as teaching intensity increases.

[1] For future reference, the table below provides a match of "PPS Year" to Federal Fiscal Year Ending 9/30:

PPS: 1	2	3	4	5	6	7	8	9	10	11	12
FYE: 84	85	86	87	88	89	90	91	92	93	94	95

In 1995 the 114 academic health centers represented only 10% of all general short-term teaching hospitals, but they employed 45% of the residents. Non-academic major teaching facilities comprised 14% of all teaching facilities but employed 22% of residents, while the minor teaching sites, which comprise 76% of teaching facilities, employed 33% of residents. Residents do not usually complete all of their training at their site of employment, however, and it is not uncommon for trainees at the larger hospitals to spend 20% to 30% of their time on rotations to other hospitals and to ambulatory care settings.

Table 3.1: Characteristics of Short –Term General Hospitals by Teaching Status (1995 data)

	Academic Health Centers	Other Major Teaching	Minor Teaching	Non Teaching
Number of Hospitals	114	161	855	3787
Average # Residents(*)	392	139	38	-
Average # Beds	587	537	286	117
Average Occupancy	75%	74%	62%	51%
FTE / Occupied Bed	7.97	7.25	6.94	6.27
% under 100 Beds	0%	0%	9%	55%
% Located Rural	2%	1%	13%	56%
% in Communities >2.5 m	38%	41%	25%	11%
% Facilities with:				
-certified trauma	79%	64%	29%	14%
-open heart surgery	93%	75%	43%	9%
-transplant surgery	87%	47%	17%	3%
-MRI scanning	89%	76%	60%	36%
% Investor-Owned	3%	1%	8%	16%
% Public-Owned	43%	10%	12%	30%

(*) Represents the number reported "on payroll" at each institution.
Source: AAMC Analysis of 1995 AHA Survey Data [37]

Funding for resident stipends and supervision varies by type of teaching facility but is predominantly derived from patient revenue of all types. Graduate medical

education is an apprenticeship system where trainees acquire skills while providing services under supervision. Thus residents are part of the joint production function of teaching hospitals that engage simultaneously in patient care, training and, where applicable, research. Under cost reimbursement and within less competitive markets where hospitals are still able to function as "price setters", most of the costs of education are recovered through the price structure without requiring separate identification. In this way, patients and all third party payers have historically both participated in the financing of, and received the benefits from, GME. In highly competitive managed care markets, however, payers with aggressive price negotiation strategies may be underwriting smaller proportions of GME costs, or may be avoiding them altogether by systematically avoiding contracts with teaching hospitals [38].

Costs of clinical supervision in major teaching settings can be borne either by the hospital (in the form of contracts for faculty services) or by the affiliated schools of medicine. Financial arrangements for underwriting the direct costs of GME in the smaller programs and in affiliates can take several different forms. Stipend and related costs for residents rotating to affiliated sites are sometimes underwritten by the accredited sponsoring institution and sometimes by the participating rotation site. Faculty preceptorship in community affiliates may be provided by staff of sponsoring institution, purchased by the sponsoring institution, provided on a volunteer basis by local physicians, or provided through publicly-funded regional educational umbrella organizations such as the Area Health Education Centers.

Historically, because GME costs were fully reimbursed by private and public third-party payers, little attention was paid by researchers or by health care management

to their identification or allocation. Interest in these issues kindled in the late 1970's, when Medicare program limitations on reimbursable routine nursing costs (called the "Section 223 limits") were set at a higher level for teaching than for non-teaching facilities. Interest among policy makers grew through 1981 and 1982 during the drafting of the TEFRA reimbursement legislation, which exempted direct medical education costs from the per-discharge payment limitations applicable to all acute care hospitals. It was not until Medicare transitioned from retrospective, cost-based reimbursement to the Prospective Payment System, however, that extensive research efforts began to try to understand GME funding flows and to distinguish direct educational costs from the indirect effects of educational activity on hospital operations.

3.2 Medicare Payments Under PPS

3.2.1 Hospital Payments

Payments to short term general hospitals under PPS are fixed according to a national standardized average payment per case. During the dissertation study period (through FFY 1995), the per-case amounts are set according to a standard base rate modified for local wage levels and urban location, then adjusted at the patient claim level according to a resource weight assigned to that patient's illness category ("diagnosis-related group", or DRG). For a subset of eligible hospitals additional payment adjustments are made for teaching intensity ("indirect medical education", or IME payments) and for indigent care loads ("disproportionate share", or DSH payments). The PPS base rate was developed from operating costs apportioned to Medicare in the cost reports of the 1982 federal fiscal year, averaged across hospitals and trended forward by

an annual update factor. To compute the nation's mean standardized operating cost per discharge, accounting adjustments were made to remove capital and direct medical education costs from the pool of base year costs. (These two items were returned later under separate payment schemes.) Statistical adjustments to the remaining operating costs were then made to estimate and remove the effects of area wage differences, hospital average case mix, and observed cost differentials attributable to the teaching function. The resulting national payment rates thus reflected average operating costs per Medicare discharge, standardized for case mix, regional wages and teaching status. Prior to 1992, expenses for depreciation, interest and leases were "passed through" to the provider as cost-based payments. Beginning in PPS Year 9 all capital costs were incorporated into a separate DRG-based payment scheme. Both operating and capital DRG payments were implemented by phasing in the payment change over several years, using a blend of the national rates with each hospital's historical cost per discharge. The operating payment was phased in over five years, from 1984 to 1988; capital DRGs are still in a 10-year phase-in period that will end in 2001.

Eligible teaching hospitals receive supplemental payments for graduate medical education ("GME payments") that are structured to increase according to the size and intensity of resident training in the hospital's patient care units. As shown in Table 3.2, GME payments to DRG-based hospitals were $6.3 billion in PPS Year 12, or over 8% of Medicare's total payments to short-term general hospitals. Approximately one fifth of all Medicare hospital providers receive some form of supplemental GME payment.

GME dollars are divided into two types: direct (DME) payments which cover the resident stipends, faculty supervision and related overhead costs; and indirect (IME)

adjustments to the standard DRG amounts which are designed to acknowledge higher patient care operating costs in teaching settings. Of the two, IME adjustments are more significant, accounting for 73% of the total GME payments. The GME payment supplements are an increasing portion of Medicare's total hospital payments. Payments to psychiatric, rehabilitation, cancer and children's hospitals are exempt from the DRG system. DME payments are the same in DRG and non-DRG hospitals, but IME payments are not applicable to these specialty institutions because the patient care payments are already based on hospital's own historical average cost. This dissertation is limited to the study of facilities receiving payment under the DRG method

Table 3.2: Medicare Graduate Medical Education Amounts Paid to Short Term General Hospitals ($ billions) 1989-90 to 1995-96

	PPS Yr 6	PPS Yr 7	PPS Yr 8	PPS Yr 9	PPS Yr 10	PPS Yr 11	PPS Yr 12	Average Annual % change
DME	$1.0	$1.1	$1.3	$1.6	$1.7	$1.7	$1.7	11.7%
IME	$2.5	$2.8	$3.2	$3.5	$4.0	$4.3	$4.6	14.0%
Total GME	$3.5	$3.9	$4.5	$5.1	$5.7	$6.0	$6.3	13.3%
Total Part A PPS Payments *(a)*	$53.4	$57.6	$61.3	$67.3	$70.2	$71.4	$74.7	6.6%
GME as % total	6.6%	6.8%	7.3%	7.6%	8.1%	8.4%	8.4%	

(a) Paid to all PPS short-term general hospitals, teaching and non-teaching.
Source: Author's calculations from HCRIS files. Excludes TEFRA providers.

Table 3.3 demonstrates the large variation in the level of both DME and IME payments across eligible hospitals, whether payments are measured on a per-resident, per-case or percent-of-total basis.

Table 3.3: GME Payments per Teaching Hospital: Selected Units of Measurement PPS Year 12

	Mean	Median	Maximum
GME Payments per Hospital:			
Total	$ 5.6 m	$ 1.8 m	$ 88.4 m
Per Medicare Discharge	$ 1,149	$ 603	$ 8,231
Per Resident FTE	$93,546	$83,563	$355,421
IME Adjustment, as Percent of DRG Payments *(b)*	.12	.07	.76

(b) Defined as base DRG + outlier payments, among Year 12 teaching hospitals only
Source: Author's calculations from HCRIS files. Excludes TEFRA providers.

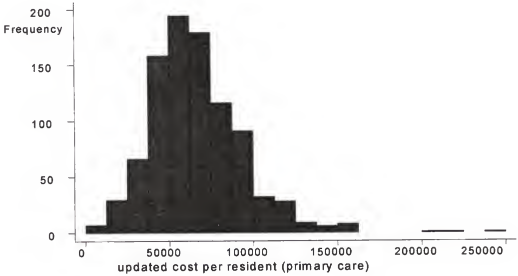
3.2.2 Direct Medical Education Payments

Medicare DME is structured as a cost pass-through, based on each hospital's updated historical average cost per resident (ACPR). The ACPR is multiplied by the total number of eligible resident FTEs at each hospital, and the result is then pro-rated by the hospital's proportion of Medicare days to total days. Components to the 1984 base year ACPR include stipends and benefits for the residents, program administration, faculty supervision, pro-rated faculty support costs incurred by medical schools if they were under common ownership, and hospital overhead as allocated to the education cost center(s) through the cost report step-down process. The DME payment method is controversial primarily because there is wide variation in unit cost across hospitals that is believed to result from differences in accounting practice rather than true economic costs [39-41]. In PPS Year 12 the mean updated ACPR on filed cost reports was $66,364, but values ranged from under $4,000 to nearly $240,000 as can be seen in Figure 3.1. Amounts at the low end of the range (below $25,000 per FTE) reflect accounting artifacts resulting from community affiliate facilities that were partially subsidized by the

sponsoring institutions in the base year of the calculation. Those at the upper end of the distribution reflect high levels of faculty supervision and aggressive overhead allocation techniques. They may also result from the inclusion of costs related to subsidized off-site residents who were excluded in the denominator, but not the numerator, in the base year computation of cost-per-FTE at the sponsoring institution.

Figure 3.1: Distribution of Updated Per-Resident Cost across Teaching Hospitals (used in computing the Direct Medical Education payments) PPS Year 12

Source: Author's calculations from HCRIS files. Sample restricted to short-term general hospitals receiving DME payments.



Medicare's historical recognition of DME is founded on the premises that a) trainees deliver services, and are therefore reimbursable under the same principles as any other input factors, b) education enhances quality, so it should be reimbursed as a unique input providing value to beneficiaries and c) medical education is a public good, whose

costs should be shared by all users of the patient care delivery system. It is the quality and public good arguments which underlie the original legislative justifications for including faculty supervision and related medical school overhead in the definition of hospitals' allowable costs in the enabling 1966 regulations for Medicare cost-based reimbursement. The exact proportion of ACPR that represents support of medical school infrastructure is difficult to derive without Medicare auditors' records from the cost reports of the GME base year. Based on expenses filed in later hospital cost reports, however, it could average no more than 30% of the ACPR amount, which would result in approximately $510 million in PPS 12. This is a relatively small proportion of the $6.3 billion in total GME payments made in that year.

By separating per-case payments into a component that is fixed regardless of resource use (the DRG) and one that can be increased by varying a particular type of labor input (the DME), an incentive may be created to favor one type of labor over another in the hospital production process. Residents can function as substitutes for several types of hospital employees. To the extent that that such labor substitution was present in the 1982 PPS base year, DME payments represented a "cost carve-out" but not an additional Medicare payment responsibility. There is a potentially strong incentive during any period subsequent to 1982, however, for hospitals to use new residents in place of employees of the type who were present in the DRG base year cost calculations. Medicare regulations included only one explicit proscription against DME payment in circumstances of intentional resident labor substitution, applicable in the case of anesthesia trainees who are hired to replace nurse anesthetists. In my search of the literature I found no empirical studies of resident/nurse substitution that investigated

within-hospital post-PPS increases in teaching intensity and staffing ratios for nursing or other employees.

In 1987 and again in 1993 minor regulatory changes were implemented for DME to reduce the per-resident amounts paid for sub-specialists and other specialties with training programs lasting over five years. These changes had a relatively small impact on total dollars paid [42] and to date I have found no published studies of the impact they may have had on the distribution of training slots by specialty. For the years under study (1984 -1996) there were no other regulatory restrictions on the numbers or types of residents eligible for Medicare payment at any given hospital, provided the trainees had passed all required exams and the rotations were part of an accredited program meeting the standards of the appropriate residency review committee.

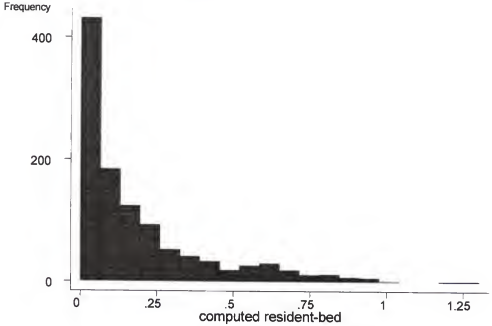
3.2.3 Indirect Medical Education Payments

The term "indirect medical education costs" refers to observed Medicare operating cost differentials that correlate with teaching intensity as measured by the ratio of residents to staffed beds. The Indirect Medical Education (IME) payment adjustment is structured to reflect these cost differentials, as a similarly increasing function of teaching intensity. The adjustment was empirically derived by HCFA analysts from the parameter estimate on a teaching intensity variable, in a multivariate regression model of Medicare hospital costs that controlled for case mix, urban location, hospital size and local wage variation [43]. In these cross-sectional (single-year) analyses of average hospital costs, the teaching differentials were found to be an increasing function of the ratio of interns and residents to staffed beds (the IRB).

The IME adjustment formulas that were eventually incorporated into the DRG payment system were constructed from the IRB parameter estimates in HCFA's cost model. Congress deliberately made the adjustment larger than the observed relationship by a factor of two (later reduced to 1.89) in order to accommodate industry concern about the effects of PPS on the finances of the teaching hospitals as a group.

Teaching intensity, as measured by resident-to-bed ratios, is a highly skewed variable. One half of teaching hospitals had ratios below 0.10 in 1995. AHCs commonly have ratios between 0.5 and 0.7, resulting in incremental payment adjustments of between 30% and 45% of the weighted DRG amount. As Figure 2 demonstrates, there are a few outlier facilities with IRB ratios over 1.0.

Figure 3.2: Distribution of Intern & Resident Bed Ratios Across DRG-based Teaching Hospitals, PPS Year 12



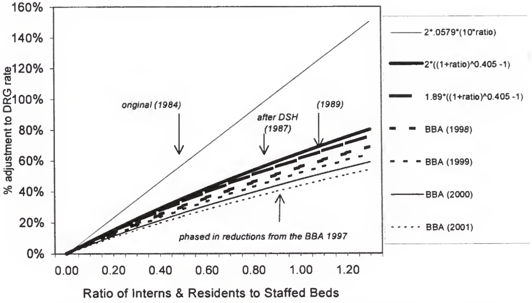
Source: Author's calculations from HCRIS files, as derived from IME payment rates

IME payments have been a source of controversy since the DRG payment system was first proposed, both because of the politically derived exaggeration of the original rate and because of disagreements over the specification of the models used in the derivation of the adjustment factor. In HCFA's original regression models, which used log transformations of both dependent and independent variables, the coefficient on teaching intensity was 0.0579. HCFA's interpretation of this was as follows: comparing across hospitals and controlling for case mix, regional wage variation and urban location, per-case costs were 5.79% higher for each 0.10 point increase in the IRB ratio. For the first three years of PPS Congress doubled this effect in the payment regulations, creating a payment adjustment factor of 11.59%. A hospital with an average of 1 resident for every 10 beds (IRB = .10) received an 11.59% increase to the federal portion of its DRG payment. A hospital with an average of 1 resident to 2 beds (IRB = .50) received a 57.95% (= 5 *11.59%) adjustment.

The IME formula has been reduced several times since 1983, as illustrated in Figure 3.3. The most substantial modification occurred in 1987 when a separate DRG payment adjustment was introduced to provide additional compensation to hospitals with high indigent care loads. For lack of a more direct measure available through the cost report, indigent care loads were proxied using a sum of the proportion of total patients covered by Medicaid and the proportion of Medicare patients who were eligible for Supplemental Security Adjustments. A formula derived from this figure was developed, called the "disproportionate share adjustment" (DSH). DSH absorbed a significant portion of the cost differentials that had been observed across levels of teaching intensity. The DSH adjustment reallocated DRG payment increments to both teaching and non-

teaching facilities. The 1987 legislative changes also modified the way in which HCFA's model results were used to calculate the adjustment factor specific to each hospital, to reflect the non-linear relationship implied by the logarithmic functional form. A new model was run on the same 1981 Medicare discharge data, but including a variable to represent disproportionate share obligations. It generated a coefficient of 0.405, reducing the estimated effect of teaching intensity to 4.05% per 0.10 increment in the ratio. The cost impact is calculated as $(1+\text{IRB ratio})^{.405}$, which produces a slightly declining marginal impact of increased teaching intensity.

Figure 3.3 History of Indirect Medical Education Payment Formulas under the Prospective Payment System *(Operating DRG Adjustment only)*



Source: Formulas derived from ProPAC Technical Report [44] and from the Balanced Budget Act of 1997 [45]

The congressionally mandated payment adjustment factor continued to double the effect measured by the empirical work, until 1989. After that the payment adjustment was computed as 1.89 times the estimated cost impact from the 1987 cost model. This formula remained in effect until the Balanced Budget Act of 1997. The "average" IME adjustment figure of 7.7%, which is often referenced in policy literature and the media, derives from the product of (1.89 × .405). It is technically accurate only for the payment increment in a hospital with a 0.10 ratio. For each .10 increment in teaching ratios beyond that, the additional payments are slightly less than 7.7% of the DRG amount.

The IME payment adjustment is calculated annually from the hospital's IRB ratio, then applied to the weighted DRG payment appropriate to each individual claim. The total IME amount received by a hospital, *per resident hired*, is thus a function of the number of residents, the number of staffed beds, the proportion of Medicare discharges to total and the average DRG weight of its Medicare case-load (called its "case mix index", or CMI). Because of the non-linear form of the model, incremental payments received per additional trainee are higher for the first resident hired than for subsequent residents, but the differences are not great.

Table 3.4 demonstrates this by modeling the marginal payment effects of adding new residents in different types of hospitals. It assumes a base DRG payment rate of $3,500, while varying other assumptions regarding Medicare utilization rates and the number of new residents hired. From the perspective of a hospital manager making sponsorship decisions, the potential "reimbursement return" for the last resident hired is most sensitive to changes in the total volume of Medicare patients and in the average DRG weight.

Table 3.4: Marginal Payment Effects of Adding Resident FTEs for Four Types of Hospitals

For each hospital: assumes base DRG payment of $3,500 per case with DRG weight = 1.00; occupancy = 75%; average length of stay = 8 days.

	Adding 1 Resident	Adding 10 Residents	Adding 25 Residents
Hospital A: 500 beds, 250 residents (ratio=0.50) with an average case mix index of 1.80:			
Point Increase in DRG Adjustment %	0.1 %	1.2 %	3.0 %
Additional $/Medicare Case	$ 7.57	$75.47	$187.59
Additional $/ 1 Resident:			
if Medicare utilization=40%	$51,838	$51,655	$51,354
if Medicare utilization=20%	$25,919	$25,827	$25,677
Hospital B: 400 beds, 120 residents (ratio=0.30) with an average case mix index of 1.60:			
Point Increase in DRG Adjustment %	0.2 %	1.6 %	4.0 %
Additional $/Medicare Case	$ 9.16	$91.16	$225.99
Additional $/ Resident:			
if Medicare utilization=40%	$50,163	$49,908	$49,492
if Medicare utilization=20%	$25,086	$24,958	$24,750
Hospital C: 150 beds, 15 residents (ratio=0.10) with an average case mix index of 1.20:			
Point Increase in DRG Adjustment %	0.5 %	4.7 %	11.6 %
Additional $/Medicare Case	$23.58	$232.13	$565.98
Additional $/ Resident:			
if Medicare utilization=40%	$48,417	$47,657	$46,479
if Medicare utilization=20%	$24,220	$23,840	$23,251
Hospital D: 100 beds, previously non-teaching, with an average case mix index of 1.10:			
Point Increase in DRG Adjustment %	0.6 %	6.2%	15.1 %
Additional $/Medicare Case	$26.72	$261.54	$632.31
Additional $/ Resident:			
If Medicare utilization=40%	$43,909	$42,972	$41,556
If Medicare utilization=20%	$21,941	$21,473	$20,765

Source: Author's Calculations

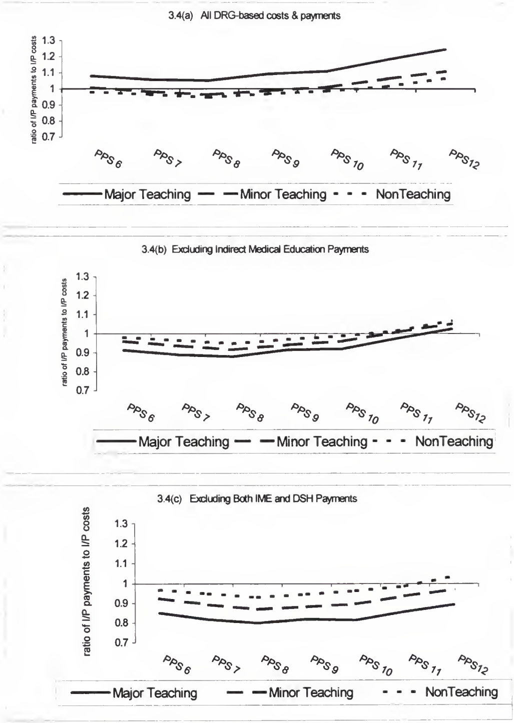
3.2.4 Trends in Medicare Payment and Costs

The average margin of Medicare payments over patient care costs dropped dramatically through the first seven years of PPS, but improved for all types hospitals after that time [46]. This is primarily attributable to a strong secular trend of decreased length of stay and declining rates of increase in real cost per Medicare discharge since 1990. Updates to the DRG payment rates are not directly tied to changes in the average cost per Medicare discharge. Instead, the federal rates are increased annually according to HCFA's index of hospital input prices, with modification for the estimated effects of technology, DRG coding changes and corrections for errors in prior year inflation estimates. In theory, cost reductions attributable to industry-wide changes in length of stay or intensity of service use should be retained, or at least shared, by the industry.

The graphs in Figure 3.4 show how the ratio of total Medicare PPS payments to hospital costs has changed in the period from PPS Year 6 to 12, across hospitals grouped by teaching status. (This period is chosen because Year 6 is the first year in which hospitals were paid based on 100% of the federal prospective rates. A small number of rural hospitals continue to be paid based on a blend of hospital-specific with federal prospective rates.)

Figure 3.4: Mean Medicare Payment-to-Cost Ratios Under PPS by Teaching Status, With and Without IME and DSH Adjustments

Includes operating and capital payments and costs, but excludes direct medical education and organ procurement. Computed from short-term acute care facilities with >25 Medicare discharges.



Source: Author's calculations from HCRIS files.

On average, the ratio of PPS payments to costs has always been higher for teaching than for non-teaching institutions. From Figure 3.4 it is also evident that the margins have increased somewhat faster for teaching hospitals than for non-teaching hospitals, and faster for major than for minor teaching hospitals. This suggests that the IME payment formulas are increasingly overstating the indirect costs of teaching.

The widening gap in payment margins may result from the way in which the PPS legislation implemented the IME formula. The indirect cost association identified by the earlier single-year studies was incorporated into the payment system by law and not altered from 1987 to 1997. The adjustment factor of 0.405 did not change, but hospitals' IME adjustment rates were allowed to be re-computed each year, using annually updated resident-to-bed ratios. If Hospital A had an IRB ratio of 0.10 and Hospital B had one of 0.20, Hospital B's adjustment rate was 1.89*4.05, or 7.7 percent points higher than Hospital A's adjustment rate. Similarly, if Hospital A increased its ratio from 0.10 in one year to 0.20 in the next, Hospital A's IME adjustment rate would be raised by the same 7.7 percent points. Thus the formula implemented the payment differentials as though the research had demonstrated that the effect of teaching intensity on cost applies within hospital as well as across hospitals. If the longitudinal association is not present, the mechanics of the IME formula will increasingly overpay those hospitals that raise their ratio of residents to beds.

Overstatement of the IME adjustment, however, is only one possible explanation for the widening differentials in Medicare payment margins during this period. If IME payments are excluded from the calculation, as in Figure 3.4(b), the payment ratio still improves fastest for major teaching facilities. Part of the improvement in margins is

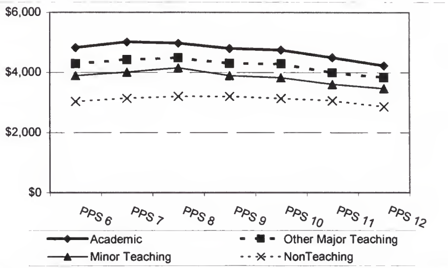
attributable to increases in the level of Medicare DSH payments, which are tied to hospital Medicaid utilization. DSH payments rose dramatically when Congress mandated expansions in Medicaid eligibility during the late 1980's and early 1990's. As the proportion of hospitals eligible for DSH adjustment is nearly twice as high among teaching facilities than non-teaching facilities, Medicaid expansion created a clear Medicare payment advantage for the teaching hospitals. If both IME payments and DSH payments are excluded from the ratio calculation, as in Figure 3.4(c), the rate of improvement in payment margins appears more stable across the three groups of hospitals.

The relative improvement of teaching hospital payment margins is at least partially attributable to stronger cost reductions among larger teaching institutions. Figure 3.5 depicts trends in real cost per Medicare discharge, after adjusting for changes in the case mix index. The rate of reduction in adjusted costs averaged less than 1% per year over the six-year period for non-teaching hospitals, but was twice that rate for non-academic teaching hospitals. In academic health centers, cost reductions averaged 2.1% per year.

Case mix adjustment is necessary to this analysis because the average hospital DRG weight has risen more quickly among major teaching facilities. The CMI increase may reflect true increases in relative patient acuity, but it could also be the result of more sophisticated coding techniques. If the latter is true, then the steeper reductions in teaching hospital costs that are shown in Figure 3.5 would be an artifact of the DRG system, yet would still help to explain the stronger relative improvement in payment margins among teaching hospitals.

Figure 3.5: Case-Mix Adjusted Real Medicare Cost Per Discharge, by Teaching Status

Hospital Average Cost/Discharge adjusted to 1987 dollars by PPS Input Price Index; divided by hospital average case mix index.



Source; Author's calculations, HCRIS files

Moderately favorable trends in cost reduction among teaching as compared to non-teaching hospitals are evident across PPS Years 6-12 regardless of price or case-mix adjustment, as shown in Table 3.5.

Table 3.5: Percent Change in Medicare Cost Per Discharge, PPS Years 6 – 12, by Teaching Status

	Non-Teaching Hospitals	Minor Teaching Hospitals	Major Teaching Hospitals, Non-Academic	Academic Health Centers (AHCs)
Unadjusted Cost/Discharge (current $)	+ 19.0%	+ 15.9%	+ 17.9%	+ 16.3%
Unadjusted Cost/Discharge (1987 $)	– 1.3%	– 4.1%	– 2.7%	– 2.5%
CMI-Adjusted Cost/Discharge (1987 $)	– 5.8%	– 10.8%	– 10.5%	– 12.4%

Source: Author's calculations from HCRIS files.

During this same six-year period, the IRB ratios used to compute IME payments on the submitted cost reports increased by an average of 21% [2]. By teaching status, the increases were 18% for minor teaching facilities, 37% for non-academic major teaching facilities and 25% for academic health centers. The downward trends in average cost per discharge, occurring simultaneously with increases in the IRB ratios, suggest that increases in teaching intensity *over time* may not be associated with increased cost per discharge, or at least may not have as strong an association as has been observed in cross-sectional studies. Because there is also a secular trend of reduced length of stay resulting in lower costs per discharge across *all* hospitals, it is difficult to draw conclusions regarding the independent role of teaching intensity on costs, from this type of analysis on grouped data.

[2] Based on an un-weighted average across all teaching hospitals eligible for IME payments.

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4 Literature Review and Prior Work

4.1 Surveys of Hospital and Educational Program Decision-Makers

There is a limited amount of literature directly addressing the factors that motivate teaching decisions among hospital and medical school leaders. In 1995 the AAMC sent an eight-page questionnaire to the directors of all internal medicine teaching programs to gather information on recent or projected changes in program size and specialty configuration [47]. Because internal medicine accounts for 30% of all residents and includes generalist and specialty trainees, plans within this subgroup may reflect more general GME trends. Of 418 programs surveyed, 335 (80%) responded. During the period covered by their questions (1993 to 1995) AAMC found that more programs had added residents than had reduced them. Of the 260 programs that neither reduced nor planned to reduce trainees, 111 provided reasons for their decisions. Forty-seven percent stated that they had "no need" to reduce, in that they experienced no difficulty filling positions or placing graduates. Eighteen percent cited potential difficulties meeting inpatient service requirements at their respective hospitals. Several respondents noted that concurrent pressure to move training into ambulatory environments was already placing stress on inpatient units that were accustomed to resident coverage. Fifteen percent said their programs were already at the minimum size needed to meet residency ACGME/RRC accreditation requirements. Five percent indicated that they were actually in "growth mode".

In the responding sample, plans for reconfiguration to replace specialist with generalist training were only slightly more common than plans for reductions in total numbers of trainees. One hundred seventeen programs had converted positions to generalist or primary care training slots, but the majority of conversions were from the one-year preliminary tracks that provide mandatory medical training prior to entering other specialist fields (e.g. radiology or anesthesia), rather than from the medical subspecialty programs.

A follow-up survey in 1996 confirmed these trends. Eighty-one percent of responding programs reported "reviewing" their program size; 65% of those who undertook reviews concluded that reconfiguration was necessary, but that their actual or planned reductions in sub-specialties were in most cases to be replaced with additional generalist trainees. This is similar to the pattern found by Dunn and Miller [48] when analyzing AMA data for all GME programs from 1996 to 1997. These authors found that reductions in anesthesia and certain medical subspecialties were offset by expansions in primary care programs and in the newer emergency medicine and physical medicine programs. Nevertheless by the beginning of 1996, before any substantive GME payment changes had been implemented by the Medicare program, the total number of residency slots in US hospitals had at least stopped increasing. The pattern of reductions and expansions in slots across programs suggests that GME program directors may be responding to market signals in the composition, if not in the absolute level, of the trainee workforce.

A study published in Academic Emergency Medicine surveyed 70 medical school deans, 102 GME committee chairs and 97 hospital CEOs at sites that sponsored

emergency medicine training programs. Their purpose was to determine institutional responses to a hypothetical 25% cut in GME funding [49]. Although the authors were primarily interested in determining whether emergency medicine training was at disproportionate risk for reductions, the survey provides some insight into GME decision-making across specialties. Unfortunately the survey did not offer respondents an opportunity to answer "no reductions" in response to reduced funding. The investigators assumed that reductions would take place, and their survey provided several options for first and second choice on how to allocate the reductions across programs. Overall survey response rate was 74%. Consistent with AAMC findings, the authors found only 1% of respondents supporting primary care reductions and only 16% favoring proportional allocation of cuts across all specialties. Twenty percent of respondents advocated targeting whole programs for elimination rather than reducing the size of existing programs (13% favoring elimination of all training programs at a given site, 7% favoring closing only specific specialty programs within a site). The remaining 63% of responses advocated targeted reductions in specialties perceived to be in over-supply, with anesthesiology, pathology and radiology heading the first-choice list among all three types of respondents. Emergency medicine (a relatively new specialty receiving accreditation in 1989) was in the middle of the ranked list.

A "Workgroup on GME Sizing" within the AAMC has published a resource guide for AAMC member institutions who are considering major reductions in training [50]. The guide includes nine case studies of facilities that have recently "down-sized" or "re-sized" 1. Data were obtained from structured telephone interviews that were

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1 The sites were: Partner's Health Care System (Mass General/Brigham & Women's); The Henry Ford System; Duke University Medical Center; Maimonides Medical Center; Maine Medical Center;

designed to elicit information on the assessment and planning process, the methods used for allocating reductions across specialties, the methods used for meeting continuing hospital service needs, and the overall financial effects. All nine facilities began evaluating the size of their programs during the mid-nineties when there was considerable discussion of physician over-production. Each site reported believing, at the time, that GME payments would be reduced in the near future. The evaluations were initiated by hospital CEOs in only two of the nine cases — Duke University (where the hospital and university are under the same CEO) and Partners Health Care System in Boston (which had recently acquired Massachusetts General Hospital and Brigham & Women's Hospital). In all other cases, various levels of educational leadership initiated the residency program reviews. All but one of the case studies cited national or regional physician workforce concern as a significant motivating factor in conducting the reviews. Most indicated that at the time the reviews were started, their leadership believed that there would be some form of legislative control over residency training in the future. Only the Henry Ford System acknowledged having concern about the quality of its educational programs, and their failure to attract U.S. medical graduates, as principal reasons for considering training reductions.

The roles that financial considerations played in these deliberations were somewhat contradictory. Reviews that were dominated by academic departments talked about fears that the faculty professional practices would not be able to support stipends and supervisory costs if Medicare made substantial cuts. Where academic interests had key decision-making roles, the financial perspective seems to have been limited to

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University of Minnesota Medical School; The University of Colorado Health Sciences Center; the Robert Wood Johnson Medical School; and the Department of Veteran's Affairs (as a system).

concerns about funding direct costs; indirect medical education costs as well as payments were often overlooked. Several sites did not involve hospital financial staff in the discussions at all, and six out of nine admitted that they failed to predict the total financial impact on the hospital's Medicare payments. Duke Medical Center had set a target of a 30% reduction in trainees (about 250 FTEs), but stopped after 12-15% was implemented, stating that better data were needed to "assess the cost-benefit" status of the plan. At the Henry Ford System, hospital financial management appeared to have predicted the reimbursement impact accurately, but not the replacement costs. They estimated that reducing internal medicine training by 12 FTEs (the first round in a planned reduction of 36) resulted in a *net* cost of $3 million in the first year, including $1.5 million in lost Medicare payments. At Partners Health System, the residency review appeared to be an integral part of hospital management's attempts to eliminate duplication following their merger of two of Boston's major academic medical centers. Expecting a significant reduction in total hospital services delivered, the CEO ordered a 20% training reduction (more than 200 FTEs) over a five to seven-year period with no expected replacement staff. By 1997, however, inpatient services had not declined as predicted. Interviewees acknowledged that the cost of resident replacements would have to be factored into future residency restructuring plans.

Every site acknowledged that its planners had underestimated the impact of trainee reductions on service delivery, attending physician workload and professional replacement costs, particularly since many specialty-board RRCs were attempting to limit resident work hours during this same period. Expected methods for coping with the loss of resident labor that were mentioned in the case studies included hiring mid-level

practitioners, hiring salaried in-house physicians ("hospitalists"), enforcing more intensive faculty patient care effort, extending resident moonlighting hours, and re-engineering patient care units for more efficient coverage. Partners Health System acknowledged accomplishing reductions in part by cutting back on off-site rotations and electives. This approach has the effect of passing on both the reimbursement and the service delivery impact of reductions, to the affiliate teaching hospitals.

Findings from these case studies may not be generalizable to affiliates or minor teaching sites. AAMC notes that the institutions that were most successful at implementing reductions were those with strong leadership and enough financial resources to underwrite extensive replacement costs. It could be argued that these institutions represent the best patient care and educational sites in the country, which raises the question of whether it makes sense to reduce training in these sites rather than in sites of marginal quality. John Iglehart, an editor of the New England Journal of Medicine and frequent contributor to the debates over Medicare reform and graduate medical education, raised similar concerns over the initial implementation of Residency Reduction Incentive plans in New York State [51]. He noted that several of the community-based, IMG-dependent training programs declined to participate in the demonstration program.

The North Carolina Rural Health Research and Policy Analysis Center conducted a telephone survey of administrators in rural teaching hospitals. The survey's primary objective was to assess the potential impact of Medicare funding reductions on rural GME sites [52]. A total of sixty-seven acute-care facilities in non-metropolitan counties were identified as having received Medicare GME monies during PPS Years 11 or 12, of

whom 33 agreed to participate (response rate of 49%). Two of the responding institutions were tertiary-level rural referral centers, but the remaining hospitals represented typically small teaching programs sponsoring mainly primary care, general surgery or emergency medicine residents. Administrators' perceptions of the effect of residency sponsorship on hospital operations were predominantly positive. Table 4.1 summarizes their responses to a set of questions designed to identify the impact of training on quality of care and physician satisfaction.

Table 4.1: Perceived Benefits of Medical Residents to Rural Hospitals

	Number of Responses	Much Better	Better	No Impact	Worse	Much Worse
Quality of Patient Care	32	25%	41%	34%	0 %	0 %
Patient's Perception of Quality of Care	42	19%	41%	41%	0 %	0 %
Hospital's Ability to Recruit Staff Physicians	36	34%	38%	14%	0 %	0 %
Staff On-Call Hours, for Services w/ Residents	42	28%	31%	38%	0 %	3%
Hospital's Ability to Retain Staff Physicians	32	28%	28%	44%	0 %	0 %

Source: Working Paper No. 56, North Carolina Rural Health Research & Policy Analysis Center

Of the 33 responding hospitals, 57% reported having residents on their own payrolls, an indication that they were sponsoring their own accredited programs rather than acting as off-site rotations for other institutions. When asked to predict their response to a possible elimination of Medicare IME payments, 51% indicated they would reduce or eliminate their programs, 27% believed there would be no change and the remainder were unsure. Responses to the same question with regard to DME payments were similar. With 43% of respondents receiving residents on rotations from other

programs, however, it is likely that residency training decisions in rural sites are heavily influenced by the objectives of the larger sponsoring institutions.

4.2 *Studies of Teaching Hospital Costs*

4.2.1 Behavioral Cost Functions

The HCFA hospital cost models as developed by staff economists Julian Pettengill and James Vertrees [53] were based strictly on cross-sectional studies of average cost behavior. They contained no production functions (that is, it did not model factor inputs) and were not based on theories of hospital optimizing behavior. Pettengill's primary task was to develop reliable resource weights for diagnosis related groups. His analytic focus was on testing the estimate, variance and stability of the parameter on the case mix index variable. The OLS estimating equation was:

Equation 4.1:

$$\ln(\text{oper costs}) = \alpha + \beta_1 \ln(\text{CMI}) + \beta_2 \ln(1+\text{IRB}) + \beta_3(\text{Wage Index}) + \beta_4(\ln \#\text{beds}) + \beta_5(\text{urban status})$$

where:

oper cost = average hospital operating costs per case
CMI = hospital case mix index (average DRG resource weight)
IRB = hospital's ratio of residents to staffed beds.

The hospital was the unit of analysis and the cost and CMI variables were arithmetic means within hospital, per Medicare discharge. The IRB is valued at 0 for non-teaching institutions; a constant of 1.0 was therefore added to all IRB values prior to computing the natural log.

The IRB ratio was originally entered into the model in order to control for what the analysts believed was inefficiency due to legitimate "learning curve" factors

attributed to the presence of trainees. It was also acknowledged to serve a proxy to control for differences in within-DRG severity. The model coefficient on the teaching variable was immediately incorporated into the mechanics of the DRG payment calculation. Congress' reasoning, as stated in the enabling legislation, was as follows:

> This adjustment is provided in light of doubts…about the ability of the DRG case classification system to account fully for factors such as severity of illness of patients requiring the specialized services and treatment programs provided by residents…The adjustment for indirect medical education costs is only a proxy to account for a number of factors which may legitimately increase costs in teaching hospitals.
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> House Ways & Means Committee Report, No. 98-25, March 4, 1983 and Senate Finance committee Report, No. 98-23, March 11, 1983. *As reported on page 6, in [54].*

A later version of the estimation, referred to as the "payment model", also controlled for outlier payments, and restricted the values on the CMI coefficient to 1.00 and on the wage coefficient to 0.75. The payment model was designed to conform to the actual conditions of the DRG claim payment.

A series of critiques appeared after the publication of Pettengill's research in 1982, re-analyzing the HCFA model to test for omitted variables and other specification errors that might affect payment equity under PPS. As stated by Kenneth Thorpe:

> When regression analysis is used to set payment rates, model specification and its subsequent interpretation represent key policy choices. Thus, econometric errors transcend purely academic interest; indeed, they may generate dysfunctional reallocations of payments across hospitals.
>
> (in [55], *page 222)*

Gerard Anderson and Judith Lave [56] published the first comprehensive critique of the teaching coefficient in 1986. They were concerned that a variable denoting hospital size was included in the model, but not in the payment formula; because the coefficient was positive, this had the effect of penalizing large hospitals in the

distribution of adjusted DRG payments. They also suspected that HCFA should distinguish between cost effects of teaching intensity and possible cost effects of serving poorer populations, since these characteristics were correlated. And finally they were concerned with potential insensitivity of the MSA-based wage index to costs associated with urban intensity and city size. The authors repeated HCFA's regression using the same 1981 hospital data but they successively removed or entered new variables to address each of these concerns. Using Pettengill's identical specification they obtained an IRB parameter estimate of 0.52 (s.e. 0.10) as compared to Pettengill's 0.569 (s.e. 0.04), which they attributed to differences in data edits and exclusions. Adding dummy variables for inner city location and measures of the percent of population below the poverty level reduced the coefficient by about 10% to 0.47 and improved its precision, from which they concluded that the original model suffered from significant omitted variable bias. Acknowledging that Congress may have intended for inner city hospitals to receive additional payment, however, they recommended that the payment formula be modified to separate the effects of teaching from those of serving high poverty populations. (This suggestion was incorporated the following year into the Omnibus Budget Reconciliation Act of 1987, as the Disproportionate Share Adjustment (DSH) to the PPS payment regulations.)

The mechanics of the HCFA payment model are such that if a variable is included in the estimating equation, is significant and is included in the payment formula, then DRG payments will be adjusted to reflect the distribution of the variable across appropriate hospitals. If a variable is included in the equation but excluded from the payment formula then hospitals are at risk, according to how they manage this particular

variable. If a variable is related to the outcome, correlated with the regressor of interest (the IRB) yet excluded from the estimating equation, then the coefficient on IRB will be biased by including some indirect effect of the excluded item. In this way the IRB coefficient can be used to adjust payments for items that are either not directly observable (such as within-DRG acuity or costs of technology access) or are not politically expedient to acknowledge (such as regional differences in length of stay). Recognizing this, William Welch [57] and Kenneth Thorpe [55] also recreated the original and expanded versions of HCFA's regression equation, using data from later years and focussing on mis-specification from omitted variables. Thorpe was concerned with failure to control for regional differences in length of stay and with correlation between teaching status and the cost-increasing effects of non-price competition. "Non-price competition" in this context refers to the theory that hospitals will compete for admitting physician loyalty by adding equipment and sponsoring new technologies, thereby contributing to over-capacity and inefficient operations.

Thorpe suggested that since Northeastern hospitals have generally longer lengths of stay and teaching hospitals are concentrated in the Northeast, part of the observed teaching cost differential reflected regional treatment differences rather than teaching effects. Similarly, because teaching hospitals tend to be located in large cities or suburban environments with several competing hospitals, he proposed that the teaching coefficient might be measuring the effects of non-price competition rather than "necessary" costs associated with teaching environments. Each of these hypotheses was tested by adding different indicator variables to the model. The added variables resulted in significant reductions of the IRB coefficient, to levels between 0.31 and 0.36.

Thorpe also raised a question about the appropriateness of adding a value of 1 to the IRB prior to calculating its log transformation (1 being a relatively large correction factor on a series of measurements that ranged from 0.0 to 0.8). He argued that the constant correction could distort the interpretation of the variable's proportional response, which would distort the application of the coefficient to the payment formula.

Welch concentrated on differences across teaching facilities grouped according to levels of technology. He also attempted to test the explanation that part of the teaching effect reflected unmeasured patient severity by constructing models with alternative case mix adjusters. These included disease staging, severity-adjusted case mix, proportions of transferred patients and the presence of sophisticated "indicator" technologies. He found no evidence that any of these added measures reduced the estimated effects of teaching intensity, which he took as evidence that IRB ratios were not serving as a severity proxy.

Both Welch and Thorpe also suspected that the effects of teaching intensity were not log-linear but were related either to the type of teaching affiliation or to thresholds in teaching intensity. Welch concluded that a minimum threshold effect existed at about 10-15 residents (regardless of hospital size), below which no cost increments could be observed, hence no additional payments could be justified. Using different cut-points and grouping schemes, Thorpe concluded that although the coefficient on each category of teaching hospital was statistically significant, the magnitude of the effect was only sufficient to be considered "policy-significant" within the group of academic medical centers (defined as those with ratios $\geq .40$).

The most thorough technical assessment of the HCFA model was provided by Rogowski and Newhouse in 1992 [58]. These authors re-specified the model and applied

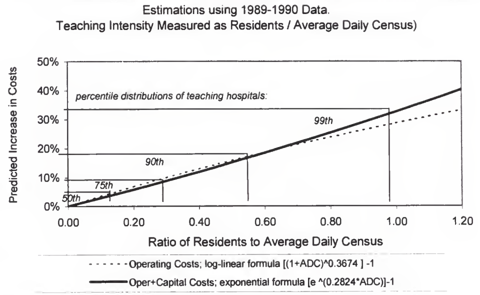
extensive regression diagnostics to test for omitted variables, measurement errors in the regressors and errors in functional form. Using hospital data from 1984, Rogowski first replicated the HCFA model (adding weights to account for non-constant variance in grouped data) and found that the coefficient had increased to 0.72. Most of their study focused on choice of functional form and on the sensitivity of the model to the additional variables identified by earlier critiques. They re-ran the model excluding beds as a predictor (to accommodate Anderson and Lave); with regional and inner-urban dummy variables (to accommodate Thorpe and Welch); and under a non-transformed linear specification of the teaching variable. They found a teaching effect that was slightly higher than those of earlier models but which behaved with similar sensitivity to added variables, and which continued to fail diagnostic tests for the absence of omitted variables. Returning to the log-log form of the models, they reduced the constant correction on the IRB variable from log(1+IRB) to log(.0001+IRB), and tested spline functions on their new form of the teaching variable in order to identify possible threshold values of teaching intensity. Their spline functions identified a cut-point around the 75th percentile of the IRB distributions, above which there was a significant increase in the strength of the teaching effect. This model was much less sensitive to additional variables, leading them to the conclusion that much of what had been identified as omitted variable bias may have been the result of improper transformation. The study also introduced smearing factors into the re-transformation of model results to payment adjustments. About the effects on the actual payment adjustments of both the modified functional form and re-transformation, however, they had the following comments:

> Although the coefficient of the teaching variable is greatly affected by changing the constant added to IRB, it is wrong to conclude that payment policy is necessarily much affected… The differences from the current formula are relatively modest, generally a few percentage points… The intuition of this is that because X is scaled differently, β is scaled differently; hence $X\beta$ is not much changed. Thus, one reaction might be that our findings are much ado about nothing. Our view is different… Our specification… appears much less sensitive to covariates. Thus, within the limitations of this paper we believe we have established a more robust estimate of the effect of teaching on cost; moreover, it is only with our modifications that one can make any claim of passing a specification test.
>
> *(from [58], page 170)*

Stephen Phillips [59], another HCFA staff economist, revisited the HCFA model to address issues raised when the regulations for prospective payment for capital costs were being finalized. The capital DRG payment formulas mirror the operating DRG formulas in that they allow for IME and DSH adjustments. The IME capital adjustment is based on the ratio of residents to average daily census, however, rather than to staffed beds. The coefficient used in the payment formula was derived from a model run on data from 1989 and 1990, which included both operating and capital costs in the outcome variable. In response to earlier criticism regarding the constant term that was added to the resident-to-bed ratios prior to log transformation, the new capital model left the teaching variable in its original (not logged) state. This results in a theoretical model that posits an *increasing* marginal effect of teaching intensity on costs — that is, it is an exponential rather than a log form.

Figure 4.1: Comparison of Operating and Capital Specifications for HCFA Indirect Medical Education Cost Models

Source: Derived from Table 2 in Phillips [59]. Percentile distributions from HCRIS files



As is evident from Figure 4.1, however, within the range of common resident-to-average census values, the differences between the capital model and the operating model are not great.

Phillips found that resident-to-census ratios performed as well as, but no better than, resident-to-bed ratios in predicting cost differentials. The coefficients are smaller because census-based ratios are necessarily higher than capacity-based ratios. The choice between these two measures of teaching intensity would not have an initial effect on the total indirect cost calculation but it would affect the growth of IME payments over time and the distribution of the IME adjustments across hospitals, according to their relative occupancy rates.

Finally, Feigenbaum, Anderson and Lave [60] attempted to investigate the effects of aggregation bias in the HCFA model. Using cost and claims data from a sample of 11,266 patients at 43 hospitals, they constructed a different behavioral cost function using similar variables as were used in the HCFA model, but adding cost and quality indicators and assuming a linear functional form. As a result, their findings are not directly comparable to those of the standard HCFA models. Their objective, however, was to compare results from a micro (patient-level) analysis, to results from a macro analysis using hospital averages for the same set of variables. Differences between micro- and macro-level parameter estimates were found in both sign and significance of the teaching as well as the location and case mix variables. The authors concluded that differences across hospitals in the underlying distributions of key policy variables create substantial bias when average values are used to derive adjustment factors that are then implemented (through the claims payment process) at the individual patient level.

4.2.2 Other Cost Models

Other researchers have approached the teaching cost problem with more general questions than were posed by those concerned only with Medicare payment equity. Responding to the question of inefficiency and the learning curve effect of new residents, for example, Dedra Buchwald and colleagues [61] designed a study at a major academic center in Boston to test what is sometimes called "the July phenomenon". Comparing resource use during early and late phases of the training year, their hypothesis was that any additional costs attributable to waste, repetition or slowness on the part of residents should be most noticeable in July when roughly one fourth to one third of the housestaff is new. Reviewing the detailed bills for over 2,700 admissions for common DRGs

between 1982 and 1984, they analyzed length of stay, cardiology testing, lab charges, pharmaceutical use, and surgery rates. The authors found very few "seasonal" differences and no overall significant pattern, but they acknowledged the weakness of a single-site investigation.

James Cameron [62] published a study in 1985 which attempted to broaden the question by a) recognizing both physician and hospital contributions to patient care cost and b) distinguishing between cost differences attributable to more intense treatment and those attributable to higher unit cost. Cameron studied combined hospital and physician resource use patterns in teaching and non-teaching facilities, using data on all non-federal hospitals in the California uniform cost reporting system and from the Medicaid claims files. He found case-mix-adjusted increments in cost per discharge of 5%, 18% and 33% for minor teaching, major teaching and university-owned hospitals, respectively. When physician billings were added to the outcome measure, however, the differences were modified to 8%, 10% and 26%. From this he concluded that substitution of trainee for professional labor was occurring, but not uniformly across all types of teaching hospitals and not to the extent that had been suspected. He also found that the differences were predominantly attributable to volume or intensity of service rather than technical efficiency. In several key cost areas including lab and pharmacy, teaching environments had lower unit costs than non-teaching environments.

Two additional studies have considered the teaching cost issue using more traditional economic theory to model the production/transformation process, in order to account for changes in the mix of inputs (particularly physician inputs) and by positing institutional behavior-optimizing models. Custer and Willke [63] examined the effects of

medical staff characteristics on the cost of care in teaching hospitals in a model that acknowledged graduate medical education as both an input and an output. Hospitals were assumed to be minimizing patient care costs subject to a constraint of externally derived training production goals. Their study is unusual primarily for its inclusion of variables reflecting estimates of specialty-specific physician time spent in patient care, teaching and research. The physician data were derived from an AMA survey.

The authors approached their questions from both a theoretical and policy perspective. They were interested in the effects of medical staff characteristics (gender, age, years since training, foreign status and specialty) and medical staff participation (time allocations to teaching, patient care and other activities) on the teaching intensity-operating cost relationship. They ran three specifications of their basic production function: (1) without medical staff information, (2) with information on medical staff demographics only, and (3) with demographics plus a labor input proxy based on survey results from the "percent physician time spent" field of the AMA survey. Although their empirical specification is lengthy and over-burdened with non- or marginally significant two and three-way interaction terms, the authors return to their original policy level questions to interpret their findings in context. Using specification as close to HCFA's original model as possible, they acknowledge finding an overall increasing effect of teaching intensity on cost of about 4.6%, which is not too different from Pettengill's 5.7% or the CBO's 1987 finding of 4.0%. As in Cameron's study, including medical staff in the equation increased the cost of production, but reduced the incremental effect of residents on total cost. Custer and Willke found that the incremental effect of residents on patient care costs was inversely related to the number of full-time employed

physicians on staff and to the proportion of medical staff time that was spent on-site, delivering inpatient care. From this they concluded that the more closely residents are supervised, the less expensive they are. The authors offer the following interpretation of their production function:

> Medical staff characteristics in our model may be capturing some quality differences that would be appropriately reimbursed as part of the cost per case. The indirect costs of medical education may include the hospital's costs of attracting and retaining high-quality physicians on its medical staff.
>
> ...(The) estimated cost of residency training decreases markedly as increasingly greater detail about the medical staff is included in the estimation. It would appear that the cost of residency training is actually relatively low. Studies that find higher costs associated with teaching hospitals may be confounding the costs of residency training with other factors that are correlated... It may be, however, that these other factors, the presence of employed physicians, medical research, and physicians with greater experience, for example, may be necessary and desirable features of teaching hospitals. If more detailed adjustments to hospital reimbursement are not feasible, or would result in unintended or undesirable incentives for teaching hospitals to alter their behavior, the higher adjustments for indirect graduate medical education costs, based on simpler cost specifications, may be useful public policy.
>
> *(from [63], page 846)*

In 1995 Lehner and Burgess, from the Management Science Group at the U.S. Department of Veterans Affairs, published a study which tried to address the theoretical basis for modeling teaching and hospital costs in a VA setting [64]. VA hospitals include the cost of physicians in their accounting records, because professional staff are either salaried or paid by hospital contract. Because of the relative homogeneity of VA patients across hospitals, the authors felt that empirical findings on the teaching variables could be more easily interpreted in this environment as pure indirect education effects. To model costs these authors used a traditional Cobb-Douglas production function of $y = AL^{\alpha}K^{\beta}e^{\mu}$ (where y is total cost and L and K are a series of labor and capital inputs) plus an indicator variable for teaching status. Resident FTEs, and physician FTEs active in direct patient care or in resident supervision, were included as continuous variables in the labor

vector. Although traditionally a Cobb Douglas function uses squared and cubed terms of the cost input variables, the authors claimed that higher order terms were not jointly significant in this data and so were eliminated. This reduced the equation to a log-log specification very similar to the original HCFA model but including multiple factor inputs. The authors were cautious about their results but were willing to state that teaching status had an independently negative effect on both hospital and physician productivity. It was not as high as HCFA regression estimates had measured, but what they identified was still higher than what had been measured by earlier accounting-style estimates within individual VA departments.

4.2.3 Residents and Labor Substitution

Literature addressing the potential impact of resident reductions on hospital operating costs is directly relevant to the question of the role of reimbursement incentives in hospital teaching decisions. Several studies have been published in the last five years addressing the hospital employment and cost implications of reductions in the numbers of residents and in the average worked hours per resident. Knickman *et al*. [65] studied internal medicine residents in two major urban centers. They concluded that only 11% of residents' time was spent in activities normally performed by hospital nursing or technical staff while 55% of their time was spent in activities normally performed by physicians, PAs or advanced practice nurses. Green and Johnson [66] extended Knickman's model to estimate the impact of proposed mandatory reductions in resident work hours throughout the New York City hospitals, arriving at estimates of annual incremental substitution costs of over $240 million. Stoddard, Kindig and Libby [67] used similar methods to estimate national costs of substitution on a per-resident basis. In

their results, the most conservative assumptions (i.e. those using the least-cost alternatives for resident labor) generated professional and technical labor combinations costing two and one half times as much as the resident. On the basis of these findings the authors recommended substantial transitional financial support to hospitals undergoing reductions in GME training.

Not necessarily in response to this research, New York did in fact negotiate a special transitional arrangement with HCFA in 1996, to cushion the IME reimbursement effects of residency reductions. Although initially criticized as evidence of political favoritism [68-70], the arrangement became the basis for the Resident Reduction Incentive Program written into the Balanced Budget Act of 1997. An Institute of Medicine committee, on reviewing the same literature, concluded that additional permanent rather than transitional hospital funding would be necessary for hospitals that were forced to reduce resident FTEs because of proposed policies limiting IMG training [71].

Each of the studies mentioned in this section focused on the effective hourly wage differentials of potential resident substitutes. An important contribution of the literature on substitution is that it directs attention to the significance of residents as replacement physicians rather than as traditional hospital employees. Attending physician costs for direct patient care are not usually included in the accounting records of U.S. hospitals and are therefore excluded from most analytic work on hospital cost functions. The expansion of graduate medical education programs over the past 15 years, however, has allowed a substantial amount of professional care to be included within the cost functions of teaching hospitals. Hospitals' motivation for incurring professional costs may be non-

financial (e.g. promoting perceived quality enhancers). The trend may also reflect the degree to which newer technologies require more intensive professional monitoring for which residents are clearly the least-cost alternative. Urban hospitals may simply be staffing clinics and inpatient wards in order to provide access to medical services for indigent communities. Whichever the reason, a thorough investigation into the economic costs of comparable levels of patient care, with the objective of comparing non-teaching to teaching environments, can only be accomplished through an integrated model that includes both hospital and professional practice costs.

Fitzhugh Mullan has recognized the essential role of residents in hospital production functions and has recommended a different type of public intervention to maintain that part of federal GME support that is related to the provision of indigent care [72] [73]. As former head of the Bureau of Health Professions he has been a frequent contributor to the debate over physician workforce needs and is a long-time critic of Medicare's GME payments. Based on average GME payments per resident FTE, he estimates that $1.37 billion in Medicare dollars can be attributed to the 26,000 international medical graduates currently in training. He advocates redirecting the Medicare savings that could be realized from reduction or elimination of IMG-related payments, to an expansion of the National Health Service Corps (NHSC) program. The NHSC is a federal scholarship and loan repayment program that places new primary care graduates in rural and urban medically under-served areas, under the auspices of the US Public Health Service. Under Mullan's plan, the NHSC would fund loan repayments and pay the salaries for new graduates of all specialties, who would work for the Public Health Service but be assigned as inpatient hospitalists and clinic physicians in facilities

serving indigent care populations. In this way the federal government could continue to subsidize professional care costs for the indigent, without creating hospital incentives to hire trainees and thus add to the future burden of surplus physicians.

Mullan's estimates of the Medicare GME amounts attributable to IMGs may be overstated when he assumes that all 26,000 IMGs are being claimed for Medicare DME and IME payments. As many as one fifth of all residents (possibly a greater proportion of IMGs) are located in VA facilities and military hospitals, or are rotating outside the hospital-based practices. During these rotations they are not eligible to be counted on Medicare cost reports. The overstatement would not alter his premise, however, that residents currently represent a low-cost solution to a factor-of-production decision in a service area that many consider worthy of public support.

Mullan's position underscores another contradiction, however, which has confused discussions of the BBA's Residency Reduction Incentive Program. Specifically, how can hospitals have historically received additional IME payments for having more residents, but now need subsidies for having fewer? The problem lies in a general confusion of direct with indirect teaching costs. Mullan proposes to reduce a hospital's Medicare receipts by an average of $70,000 per IMG resident, and then (assuming the IMG's residency slot is not filled by a domestic graduate) replace the $30,000/year-resident with a $135,000/year-hospitalist, allowing the NHSC to subsidize the hospitalist's placement in qualifying under-served areas. This approach addresses the direct GME costs and payment issues by addressing the labor substitution problems related to training reductions. Yet it ignores the extent to which IME payments function as a mechanism for legitimate product differentiation in a government-administered price

system. To the extent that the IRB serves as a proxy for fixed hospital characteristics that are related to higher patient care costs, such costs will not diminish as a residency slot is eliminated. Thus under Mullan's plan the reductions in IME payments could be considerably larger than the reductions in each hospital's operating cost, with or without subsidized professional replacements. This situation could be particularly difficult for the inner-city "safety-net" providers with which he is concerned, since their operating margins tend to be lower than those of other teaching facilities.

4.3 Prior Work: Longitudinal Study of Teaching Intensity and Hospital Costs

4.3.1 Overview

To date there are no published studies examining the association between teaching intensity and patient care costs within hospital, over time. HCFA's original analysis was conducted on data from 1981 cost reports and discharges. Several of the cross-sectional studies described in Section 4.2.1 were conducted on data from later years, but each was limited to the measured effects of a single year. There are also no systematic comparison studies in the literature that attempt to explain differences in results from cross-sectional investigations conducted over sequential time periods.

In order to gain a better understanding of the longitudinal relationships between teaching intensity and cost per case, I have re-estimated HCFA's single-year OLS model for identifying indirect medical education effects using pooled cross-sectional data derived from seven years of Medicare cost report and case mix files. By incorporating

multiple years of data, the general form of the estimating equation from HCFA's model is altered from:

Equation 4.2: $$Y_j = \alpha + \mathbf{X}_j\beta + \varepsilon_j$$

to:

Equation 4.3 $$Y_{jt} = \alpha + \mathbf{X}_{jt}\beta + \{\nu_j + \varepsilon_{jt}\}$$

where *j* subscripts unique hospitals; *t* subscripts the year in a data set with multiple observations per hospital; $\mathbf{X}$ is the vector of covariates and ε and ν are components to the model residual. The dependent and continuous independent variables in HCFA's model are log-transformed; the general model for the non-transformed data would be multiplicative, expressed as $Y=\alpha X^{\beta}\varepsilon$. Taking the natural log of both sides of the equation restates the equation in linear form suitable for least-squares estimation [74].

If the model is properly specified, ε represents an error term that has a mean of 0, a constant variance of σ^2, is not correlated with $\mathbf{X}$ and is not correlated with itself. Because of the repeated observations on unique hospitals that occur in pooled cross-sectional data, the error term for Equation 4.3 contains an additional component, ν, that is fixed within each cross-sectional unit (that is, by hospital). The total model residual of $\{\nu + \varepsilon\}$ is correlated with $\mathbf{X}$ and will not have a constant variance, violating key OLS assumptions [75]. Additional statistical controls are therefore needed in order to apply least squares multivariate techniques to panel data.

To the extent that the Medicare case mix index has become a more sensitive measure of severity (through improvement to the DRG grouping algorithms as well as more sophisticated coding) I expected the cross-sectional effects of teaching intensity to

decrease over time. That is, in later years the coefficient on the teaching variable should be absorbing less of the effects from unobserved patient acuity. In addition, to the extent that teaching intensity is serving as a proxy measure for unobserved, but primarily fixed, hospital characteristics that are associated with increased cost per case, I expected the longitudinal association *within* hospital to be to be small or non-existent. A small or non-existent within-hospital effect would also be consistent with a serially decreasing cross-sectional effect even without the influence of improved case mix measurement, in light of the secular trend of increased resident-to-bed ratios throughout this study period.

A total of 5,417 hospitals contributed 35,099 observations to a panel data set derived from the HCRIS files from the years PPS 6–12. The study sample consisted of all short-term general hospitals reporting during the period, excluding those in Puerto Rico (0.9%); those with <50 Medicare discharges (2.6%) and those with missing or inconsistent data (0.7%). Two panel data techniques were used for the analysis. The first approach exploits cross-sectional variation in a manner similar to the PPS payment model, in order to investigate year-to-year stability in estimates of the cross-hospital correlation between teaching intensity and costs, while controlling for lack of independence across observations on the same hospital unit. The second approach explicitly controls for cross-sectional variation, in order to examine the effects of changes in teaching intensity within hospitals, over time. Both models included modifications to address some of the specification errors identified by other investigators. Modifications allowed for examination of the effects of disproportionate share status and type of teaching institution, and provided additional statistical controls for analysis on group means.

4.3.2 Changes in the Cross-Sectional Correlation, Over Time

The original cost function (described by Equation 1 in Section 4.2.1) was expanded to include two additional dichotomous variables denoting eligibility for Medicare's DSH adjustment and major teaching status (defined as membership in the Council of Teaching Hospitals, or COTH). Six time trend dummy variables were added, using PPS 6 as the reference year. Each of the time trend variables was interacted with the teaching intensity variable, to test the hypothesis that the strength of the association was decreasing over time. Interaction effects for teaching with DSH and teaching with COTH status were also tested. The exact estimating equation was:

Equation 4.4:

$$
\begin{aligned}
\ln(\text{oper costs}) = \; & \alpha + \beta_1 \ln(1+\text{IRB})_{jt} + \beta_2 \ln(\text{CMI})_{jt} \\
& + \beta_3 \ln(\#\text{beds})_{jt} + \beta_4 \text{urban status}_{jt} \\
& + \beta_5 \text{DSH}_{jt} + \beta_6 (\text{DSH} \times \ln(1+\text{IRB}))_{jt} \\
& + \beta_7 \text{COTH}_{jt} + \beta_8 (\text{COTH} \times \ln(1+\text{IRB}))_{jt} \\
& + \Sigma\delta_t \text{year} + \Sigma\delta^*_t (\text{year} \times \ln(1+\text{IRB}))_{jt} \\
& + \varepsilon_{jt}
\end{aligned}
$$

where $\Sigma\delta_t$ and $\Sigma\delta^*_t$ represent the main and interacted effects of the time trend variables.

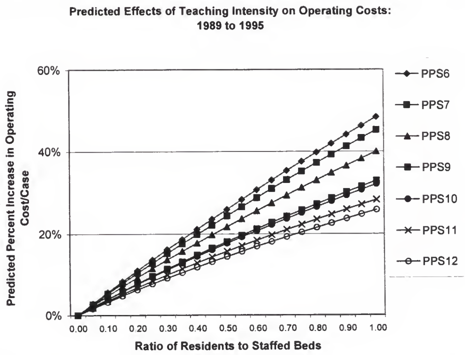
Weighted least squares regression (using the number of Medicare discharges as the analytic weights) was used to control for heteroscedasticity inherent in analysis of grouped data, because the cost and case mix variables are averages computed over hospitals of different sizes [76;77]. Control for cross-sectional correlation attributable to the panel data structure was accomplished using Huber-White standard errors with clustering by hospital identifier to allow for lack of independence across observations [78]. Table 4.2 summarizes key descriptive statistics on the study hospitals.

Table 4.2: Descriptive Data From 7-Year Study Sample, PPS Year 6-12
Total observations = N = 35,099

	All Years	PPS 6	PPS 9	PPS 12	% Change Over Study Period
Hospitals (unique n)	5,417	5,279	5,205	4,915	– 6.9%
Average Real Operating Cost per Discharge (1987$)	$3,702	3,646	$3,833	$3,500	– 4.0%
Average Case Mix Index		1.188	1.217	1.249	+ 5.1%
% Disproportionate Share Providers	33.1%	21.4%	36.0%	39.7%	+ 85.5%
% Teaching	24.1%	19.7%	20.8%	22.3%	+ 13.2%

Results from this model are depicted in Figure 4.2. (Regression tables are provided in Appendix 3.1). The graph, drawn from results before testing for the effects of DSH and major teaching status, shows that the positive effect of teaching intensity on Medicare operating costs declined steadily over the study period. The coefficient on the logged teaching intensity variable drops by over 40%, from 0.57 (s.e.=.042) in 1989 to 0.33 (s.e.=.026) in 1995. All of the time-based interaction terms after PPS 7 were significantly different from the reference year (p=.02 for PPS 8; <.0001 for later periods).

Figure 4.2: Declining Strength Over Time, in the Cross-Sectional Association Between Teaching and Operating Costs *(excludes interaction by hospital status)*



COTH membership was not a significant covariate or interaction term when included together with the DSH variables, which may simply reflect the collinearity between DSH and major teaching status. Disproportionate share status was a strong effect modifier. Among non-DSH providers, the teaching effect was one-third to one-half as strong it was among DSH providers, depending on the year. The same downward time trend in teaching effects, however, is evident in both groups of hospitals.

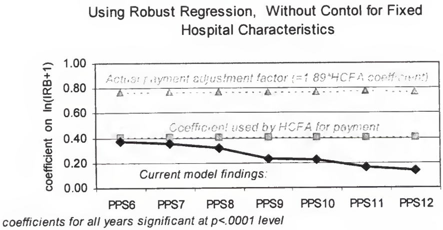
Because there is a separate PPS payment adjustment available for DSH, its effect would need to be excluded from a model of indirect medical education effects before using model coefficients to construct an IME payment adjustment. To accomplish this,

and adjust for other PPS payment exceptions in keeping with HCFA's payment model approach, the dependent variable was recomputed using Medicare costs net of both DSH payments and additional payments for length-of-stay and cost outlier cases. Results from the adjusted cost model are more directly comparable with the model used to develop the IME payment formula that was introduced in the 1987 legislation. When DSH and outlier payments are excluded from the cost base, the coefficients on the teaching variable are reduced to a range of 0.37 (s.e.=.045) in 1989 to 0.13 (s.e.=.034) in 1995.

In the model that has not adjusted cost for the DSH payments, the DSH effect is positive and significant, though of small magnitude. The indicator variable for DSH status continues to be significant in the adjusted cost model, but its coefficient changes sign, to –0.09 (s.e.=.005). A negative effect in this context can be interpreted as evidence that the DSH payments are over-adjusting for Medicare cost differentials. Such a finding would be consistent with the intention of the DSH enabling legislation; DSH payments were enacted to provide extra compensation for institutions caring for large numbers of poor patients, but were never based on documented higher costs of Medicare patients at those institutions.

A graphic comparison of these effects with those used in the HCFA IME payment formula is provided in Figure 4.3. These results tend to support earlier conclusions from the data on Medicare payment margins, that the multiplier of 2.0 (later 1.89) which Congress added to the IME payment formula contributed only to an initial PPS overpayment to teaching facilities. The widening of the gap over time is the consequence from failing to adjust the IME factor in accordance with other secular trends in teaching as compared to non-teaching hospital costs.

Figure 4.3: Correlation Between Teaching Intensity and Operating Costs Net of Disproportionate Share and Outlier Payments



4.3.3 Controlling for Cross-Sectional Effects: Within-Hospital Changes in Teaching Intensity

A weighted least squares fixed effects model was constructed to investigate the longitudinal effects of changes in teaching intensity within individual hospitals. This was carried out using dichotomous variables for each unique hospital identifier. By entering a control for each hospital, the slope parameter estimates are derived only from the variation within each hospital. The fixed effects model eliminates ν — the systematic component of the error term identified in Equation 4.3 — that is attributable to correlation within hospital units. It also controls for bias attributable to omitted variables having to do with hospital characteristics that are fixed over the time of the study period [75]. Because the model controls for fixed hospital characteristics, the teaching coefficient generated from this estimation would *not* be appropriate for use in developing

a teaching hospital payment adjustment; the resident-to-bed ratio is *intended* to serve as a proxy for fixed hospital characteristics believed to be associated with legitimate cost differentials. The fixed effects coefficient is relevant, however, for determining the most appropriate way to translate cross-sectional model results into a payment adjustment formula that is applicable over multiple years.

The general form of the fixed effects regression can be represented by:

Equation 4.5: $$Y_{jt} = \alpha_j + \mathbf{X}_{jt}\beta + \varepsilon_{jt}$$

The introduction of hospital indicator variables allows the intercept to vary across cross-sectional units (as indicated by the subscript on the constant term), while the slope coefficients remain the same. The absence of ν indicates that the model has controlled for auto-correlation attributable to the panel data structure, insofar as ν_j has been absorbed into α_j.

Because there is no possible variation in teaching intensity among non-teaching hospitals, the fixed effects model was restricted to the sub-group of 1,308 hospitals that received IME payments during the study period. Table 4.2 summarizes key descriptive statistics on the teaching hospital sub-group. To eliminate the effects of inflation, the outcome variable was deflated using HCFA's PPS Price Index. Time trend variables were retained to control for secular trends not related to inflation. The wage index was dropped from the model as it is recomputed each year to center on 1.0000 and has no interpretation as a time-based cost predictor. Urban status is also eliminated, because it is a fixed characteristic that is exactly collinear with the hospital dummy variable. As in the

cross-sectional model, interaction effects were tested for both DSH status and COTH membership.

Table 4.3: Descriptive Data From Teaching Hospital Sub-Group
Total observations = 7,516

	All Years	PPS 6	PPS 9	PPS 12	% Change Over Study Period
# Unique Hospitals	1,308	1,040	1,084	1,097	+ 5.5%
Average Resident-to-Bed Ratio	0.166	0.151	0.160	0.183	+ 21.2%
Average Real Operating Cost per Discharge (1987$)	$5,140	$5,407	$5,316	$4,794	–11.3%
Average Case Mix Index	1.421	1.361	1.435	1.475	+ 8.4%
% Disproportionate Share Providers	59.1%	46.4%	62.5%	65.3%	+ 40.7%
% Major Teaching (COTH members)	25.5%	25.5%	25.6%	24.4%	– 4.3%

The exact estimating equation became:

Equation 4.6:

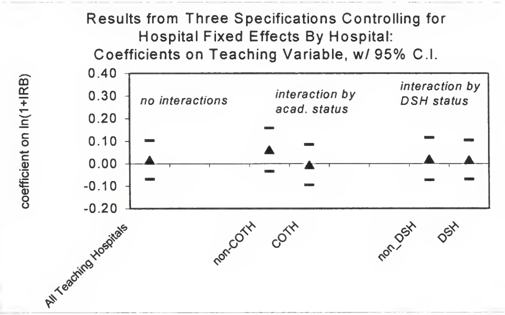
$$\begin{aligned}\ln(\text{oper costs})_{jt} = {} & \Sigma\alpha_j \text{ hospital} \\ & + \beta_1 \ln(1+\text{IRB})_{jt} + \beta_2 \ln(\text{CMI})_{jt} \\ & + \beta_3 \ln(\#\text{beds})_{jt} \\ & + \beta_4 \text{DSH}_{jt} + \beta_5(\text{DSH} \times \ln(1+\text{IRB}))_{jt} \\ & + \beta_6 \text{COTH}_{jt} + \beta_7(\text{COTH} \times \ln(1+\text{IRB}))_{jt} \\ & + \Sigma\delta_t \text{year} + \varepsilon_{jt}\end{aligned}$$

where $\Sigma\alpha_j$ represents the fixed hospital coefficients estimated by the model, $\Sigma\delta_t$ represents the main effects of the time trend variables, and the remaining variables are the same as were specified in Equation 4.5.

The fixed effects model produced no evidence of an association between changes in teaching intensity and changes in operating costs, within hospitals. The coefficient on

the teaching variable was .016 (s.e.= .059, p=.78) for the full sample of teaching hospitals. All interaction effects also tested non-significant.

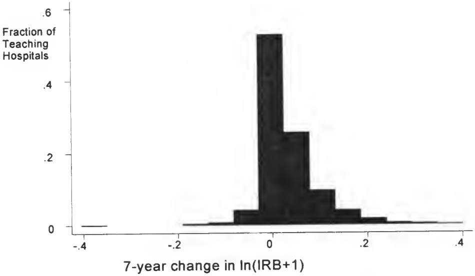
Figure 4.4 : Teaching Effects Within Hospital Over Time



As can be seen from Figure 4.4, the standard errors on the estimates were relatively large, suggesting the possibility that the negative study results could be due to insufficient variation in the teaching intensity variable. Within the study period the resident-to-bed ratio increased by approximately 3% per year, or 21% over seven years, as documented in Table 4.2. The distribution of the 7-year differences in the log-transformed value of the teaching variable, across all study hospitals, is graphed in Figure 4.5. A large proportion of the hospitals had relatively small changes in their ratios, but overall variability in teaching intensity appears substantial.

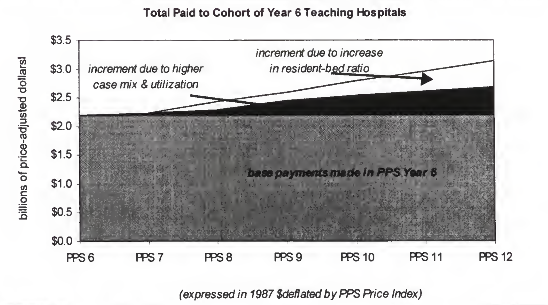
Figure 4.5: Distribution of the Teaching Intensity Variable as used in the Fixed-Effects Model

(for 1,039 hospitals that appeared in all seven years of the model)



From a payment policy perspective, one approach might be to ask the question, "are the increases in intensity big enough to have had a large budget impact on PPS payments?" The proportion of IME payments that is attributable to increases in teaching intensity — as distinct from increases in price, Medicare caseload, case mix or the number of teaching hospitals — can be derived by adjusting the IME payment data from the set of teaching hospitals that received IME payments in PPS Year 6 and every study year thereafter. Figure 4.6 presents the results of such an adjustment. Because of price adjustment, the absolute numbers on the y-axis of Figure 4.6 are less important than the proportions in the increment attributable to teaching intensity (i.e. the top layer) relative to the total area. Over the study period this segment represents roughly 8% of total real-dollar payments. By PPS Year 12, it represented nearly 14%.

Figure 4.6: Real Increases in IME Education Adjustments, PPS Year 6 — 12



A minority of hospitals experienced decreases in their resident-to-bed ratios over this period. If the payment increments attributable to IRB ratio changes were plotted by individual hospital, the distribution would be similar to that seen in Figure 4.5.

4.3.4 Conclusions

The mechanics of the IME adjustment during this period are such that DRG payments are increased to hospitals that increase their resident-to-bed ratios from year to year. If a positive association between teaching intensity and patient care costs does not exist within hospitals over time, or if such a longitudinal association is significantly smaller than the cross-sectional association on which the IME adjustment is based, then management decisions to expand graduate medical education sponsorship have the potential to generate windfall reimbursement gains. Such gains would be in addition to

any other operational or educational advantages that might be offered by expanded GME sponsorship.

Assuming that there are other, non-financial and positive utilities associated with expanded education, any reimbursement formula that increases payment according to the number of residents hired also increases the net benefit of training to the hospital sponsor. Thus, regardless of the related operating cost impact, the PPS GME payment rules have the potential to act as a financial incentives to expand training sponsorship. IME adjustments would be less likely to serve as a financial incentive, however, if the incremental payments approximated the marginal cost of residency training. Under such circumstances reimbursement increases would be offset by other increases in resource inputs, eliminating or at least minimizing the net reimbursement gain.

Results from this study provide no evidence that increases in unit operating costs are associated with increases in residency sponsorship within individual institutions. The findings provide a strong basis for investigating the long-term effects of PPS payment policy, in particular the indirect medical education payments, on the growth of graduate medical education in the United States.

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6 Data

6.1 Sources

6.1.1 Hospital Cost Report Information System

The principal data sources for this study are the Medicare hospital cost reports filed during the first twelve years of PPS implementation. The Hospital Cost Report Information System (HCRIS) Minimum Data Set is an extract from the cost reports containing data on hospital total utilization and costs, Medicare utilization, costs and payments, and simplified financial statements. Data for a given PPS year are applicable to the hospital's fiscal year that began during that PPS year. Cost reports also include information on hospital ownership and teaching status, and on the total number of resident FTEs claimed by each hospital for Medicare GME payment purposes. HCRIS files are available from the Health Care Financing Administration's Public Use Files.

HCRIS files are generally released within nine months after the close of the federal fiscal year (September 30). They are subject to subsequent quarterly updates for an unspecified period of time (usually several years), to incorporate changes made as a result of reviews, audits or corrections by either the hospital or the Medicare fiscal intermediary. Files for PPS years 1-6 (1984-1989) were obtained from HCFA in the spring of 1998; these files have incorporated most if not all corrections. Files for PPS years 7-10 were obtained at different times during their respective review processes and therefore incorporate varying levels of correction. Data for PPS years 11 and 12 were also obtained in the spring of 1998 and reflect relatively few intermediary corrections due

to delays inherent in the audit process. Table 6.1 identifies the review status of the records for each PPS year, as received from HCFA.

Table 6.1: Review Status of Cost Reports Summarized for HCRIS Data

PPS Year		Audited	Reviewed & Settled, w/out Audit	"As Submitted" by Hospitals (not Reviewed)	Unknown	Number of Hospitals
1		89.2 %	7.5 %	3.3%	<0.1%	5,797
2		87.3 %	17.0 %	7.6%	-	5,699
3		76.4 %	21.9 %	1.7%	-	5,687
4		73.7 %	25.3 %	1.0 %	-	5,657
5		60.8 %	38.2 %	1.0 %	-	5,628
6		57.6 %	40.3 %	2.2 %	-	5,516
7		25.9 %	47.3 %	27.0 %	-	5,435
8		4.9%	10.8 %	84.3%	-	5,283
9		45.2 %	52.3 %	2.5 %	-	5,302
10		22.9 %	37.5 %	39.0 %	0.1 %	5,235
11		39.6 %	55.4%	5.0%	-	5,195
12		17.3 %	26.0 %	56.7 %	-	5,117
All Years	%	50.0 %	31.3 %	18.6 %	<0.1 %	
	#	32,778	20,533	12,204	36	65,551

Source: HCRIS files. Excludes TEFRA providers

Proprietary versions of electronic cost report software have been available since the 1970's and were in common use by the first year of PPS implementation. Increasingly stringent internal data consistency edits and math checks have been programmed into the cost report software; after PPS year 6, data that is "as submitted" but not yet reviewed or audited has been subject to this internal review prior to being incorporated into the HCRIS files.

The Medicare cost report has changed substantially over the 12-year study period. Data from PPS years 2-12 have been reformatted by HCFA to conform to the variable names and definitions appropriate to year 12. Data from PPS year 1 was provided in its original layout and had to be converted to the file layout and variable definitions of the

later period. Not all variables from the subsequent periods are available for the PPS 1 year.

6.1.2 Interns & Residents Information System

The dissertation also makes use of an alternative and more detailed source for resident full time equivalents, known as the Interns & Residents Information System (IRIS). Resident FTE counts derived from IRIS files can be grouped by medical specialty, by IMG status and by year of training. IRIS data are submitted electronically by all hospitals receiving Medicare GME payments, on a data-entry program created by HCFA for GME audit purposes. IRIS data are intended for use in tracking individual residents across multiple hospital rotations, in order to assure that Medicare is not paying more than 1.00 FTE on any individual trainee. The first year of data available is 1989. IRIS files are not part of the standard HCFA Public Use Files, but tapes covering PPS Years 6 through 11 were obtained from HCFA staff in December of 1996. Year 11 appears to be only partially compiled, with less than 65% of possible teaching hospitals reporting. Year 12 was not available from HCFA as of December 1998.

Conversations with HCFA staff members confirmed that the data are used to identify possible duplications in the resident FTE counts but that reporting errors, once identified, are passed on to the local fiscal intermediaries for investigation without any subsequent corrections in the IRIS files. The files require extensive editing for duplicate rotations and inconsistent dates. Records are organized by individual resident social security number, within hospital, and contain demographic and educational data about each resident as well as the beginning and ending dates of each hospital rotation. Details regarding edits, methods for deriving the full time equivalents from rotation dates.

6.1.3 Other Data Sources

Several other HCFA data files were used in the construction of model covariates. The Provider Specific Files (PSF) contain information about each hospital that is used by fiscal intermediaries to calculate applicable DRG payment rates. They are available from the Public Use Files beginning in PPS Year 6. In the dissertation PSF data are used to construct a continuous measure for indigent care obligations derived from components to the PPS disproportionate share adjustment. Case Mix Index Files for PPS years 3 – 12 and the historical Hospital Wage Indices File were also obtained through the Public Use Files, and used in the descriptive studies on trends in Medicare costs and payment margins. The 1997 version of Medicare's Provider of Services Listing, also from the Public Use Files, was used to obtain hospital zip codes. The HCFA Office of the Actuary provided quarterly moving averages of the PPS Input Price Index from 1982 to 1996.

In addition to HCFA data, AHA Hospital Surveys from 1989, 1992, 1993, 1994 and 1995 were used to obtain zip codes on hospitals that could not be matched to the current HCFA address file because they had closed, merged or changed ownership prior to 1996 (approximately 20% of the sample). AHA variables were also used to identify non-AHC members of the Council of Teaching Hospitals. The Area Resource File (ARF) from February, 1998 was used to obtain annual physician supply variables which were then merged into the HCRIS data by hospital county code. Grant funding for bio-medical research from 1982 to 1996, by domestic medical school, were obtained from the National Institute of Health web site [77]. Funding levels were adjusted by the Biomedical Research and Development Price Index, available from the same site [78].

The AMA Accreditation Guide to Graduate Medical Education Programs (1995) [79] was used to match major teaching hospitals to affiliated research sites.

6.2 Study Population & Exclusions

6.2.1 HCRIS Sample: All Hospitals

The base study population consists of all short-term general hospitals participating in Medicare and receiving DRG-based payment during the first twelve years of the Prospective Payment System. Unique hospitals are defined by their six-character HCFA provider number. Mergers, acquisitions and other ownership changes are identified by a change in provider number and are treated as new hospitals after any new number is assigned.

Over the 12-year study period HCRIS files include data from 6,201 unique PPS hospital providers who contribute an average of 10.6 observations each. Of these, over 75% have data in all twelve years. Ninety-one percent of the hospitals appearing in PPS 12 also reported consistently from PPS 1 through 12. Reporting gaps (defined as one or more years during which a record does not appear on the HCRIS files, on a provider for which data is present in both prior and subsequent years) occur for 4% of all providers, affecting 0.4% of all observations. Table 6.2 summarizes hospital participation patterns in the data as received from HCFA.

Table 6.2: Hospital Participation in HCRIS Data, PPS 1 – 12.

# Of Years of Data:	12	11	10	9	8	7	6	5	4	3	2	1
% Unique Hospitals Contributing	75%	4%	2%	2%	2%	2%	2%	2%	2%	2%	2%	3%
% Observations Accounted For By These Hospitals	86%	4%	2%	2%	2%	1%	1%	1%	1%	-	-	-

Hospitals located in Puerto Rico were excluded from the study, as were hospitals with low Medicare volumes (defined as fewer than 25 Medicare discharges in a study year). Because the dependent variable is computed as year-to-year change, facilities contributing only one year of data over the 12-year study period are by definition excluded from computations. To ensure consistency in the calculation of change variables, hospitals with reporting gaps were also excluded for the initial year after the gap (although that year is used in computing the subsequent year's lagged variables).

Observations were excluded if there were inconsistent, missing or out-of-range values for any data *elements* used to derive the dependent variables (i.e. those related to resident full time equivalents) or the independent policy variables of interest (including Medicare DRG payments, GME payments, beds and Medicare discharges), and no reasonable correction or alternative source could be determined. Table 6.3 summarizes the effect of these initial exclusion criteria on the base study sample.

Table 6.3: Effect of Exclusion Criteria and Data Edits on HCRIS Study Sample

	# Observations Meeting Exclusion Criteria	% of Sample
Exclusions:		
Puerto Rico	439	0.7%
Low Medicare Volume	824	1.3 %
Only 1 Year of Data	182	0.3%
Gaps in Reporting	287	0.4%
Inconsistent Cost, Util., Pmt Data	899	1.4%
Inconsistent Resident FTE Data	342	0.5%
Unduplicated Count, Excluded Facilities	2,348	3.6 %
Files as received from HCFA	65,551	100.0 %
Remaining in Initial Study Population:	63,203	96.4%

In general, the earlier years of data have a higher proportion of exclusions due to missing or inconsistent values, even though more of those files had been audited. For the period from PPS 1 through PPS 9, hospitals in New York State are also disproportionately represented among the excluded providers. New York was functioning throughout the study period under a federal waiver which exempted its hospitals from the Medicare PPS payment system, in order to allow the State to experiment with a DRG-type of reimbursement from all payers. GME payment rules in New York were identical to those under Medicare, but were applicable to all payers. Although New York hospitals were still required to file cost reports, the quality of the reporting is inconsistent until PPS Year 10.

From the base set of eligible study hospitals, separate samples were constructed for the Expansion and Conversion Models. Additional exclusions were identified on these sub-samples, as data from other sources were merged and as further GME payment-

based computations revealed additional inconsistencies in the cost report data. These are described in more detail in the following sections.

6.2.2 Expansion Model Sample: HCRIS Data

The Expansion Model is restricted to Medicare PPS providers reporting residents on site or receiving Medicare GME reimbursement. Table 6.4 describes, by PPS year, the effect on the teaching hospital sub-sample of the original HCRIS exclusion criteria and the additional exclusions required by subsequently identified data problems. The majority of additional teaching facility exclusions are the result of inconsistent GME payment information or missing data from the PSF files. Some observations with adequate current year data had to be excluded because problems in their prior year data prevented the calculation of lagged and change values. Overall, nearly 16% of the sample observations and 17% of unique facilities were excluded. Excluded teaching hospitals tended to have fewer beds and smaller teaching programs than included teaching hospitals, and they were more likely to be government-owned.

Table 6.4: Effect of Exclusion Criteria on Teaching Hospital Group, by PPS Year

	Total PPS 1-12	PPS Year: 1	2	3	4	5	6
Files as received from HCFA	13,518	1,127	1,117	1,119	1,139	1,127	1,086
Unduplicated Count of Exclusions Due to Initial HCRIS Criteria	635	155	98	50	43	46	25
Additional Exclusions:							
Inconsistent/Missing GME Data	598	128	140	161	51	33	21
No Moving Av'g Dependent Var	152		21	5	10	11	10
Missing Data from PSF or Other	738		75	70	87	64	47
Remaining in Study Population	11,395	844	783	833	948	973	983
% observations excluded	15.7%	25.1%	30.0%	25.6%	16.8%	13.7%	9.5%
% unique hospitals excluded	17.0%						

Table 6.4, continued

	PPS 7	Year: 8	9	10	11	12
Files as received from HCFA	1,113	1,093	1,127	1,149	1,157	1,164
Unduplicated Count of Facilities Excluded Due to Initial HCRIS Criteria	55	16	41	31	25	50
Additional Exclusions:						
Inconsistent or Missing GME Data	15	11	10	6	6	16
No Moving Av'g Dependent Var	15	23	14	19	13	11
Missing Data from PSF or Other	53	74	71	74	79	44
Remaining in Teaching Hospital Study Population	975	969	991	1019	1,034	1,043
% observations excluded	12.4%	11.3%	12.1%	11.3%	10.6%	10.4%

Many of the exclusions occurred from the first three years of data, among hospitals that reported having residents but received no GME payments, and that did not report residents or GME payments in later years. These hospitals were probably not approved teaching sites, even in the first three years. The 10%-12% of teaching hospitals that are regularly excluded in the period after PPS 6 serves as a better measure of the proportion of true teaching facilities that cannot be included in the analysis.

6.2.3 Expansion Model Sample: IRIS Data

A subset of hospitals in the Expansion Model also has data in the IRIS files. The files are only available for PPS Years 6 through 11, and within that period, not all hospitals reported IRIS information. The original unit of observation for the IRIS files was the individual resident rotation within hospital. The six years of data as received from HCFA contained 866,693 records that were then aggregated into hospital-level observations. Table 6.5 identifies the number of PPS hospitals reporting for each year of IRIS data received, compared to the total number of teaching hospitals based on the GME payment information appearing on the HCRIS files.

Of the 6,447 hospital-level observations initially created from the IRIS files, 704 (11%) were not applicable to the study because they pertained to facilities reimbursed under the TEFRA payment rules. Another 82 (1.3%) were excluded because of incompatible dates and/or rotation times. Of those remaining, 162 did not match to any teaching hospital provider numbers from the HCRIS file, resulting in a final IRIS sample containing 5,498 observations on 1,199 unique reporting hospitals.

Table 6.5: PPS Teaching Hospitals Included in IRIS Tapes, by PPS Year

PPS Year	Teaching Hospital Observations in IRIS files	Teaching Hospital Observations in HCRIS Files (*)	% overlap
6	845	1,086	77.8 %
7	1,038	1,113	93.3 %
8	1,017	1.093	93.0 %
9	941	1,127	83.5 %
10	929	1,149	80.9 %
11	728	1,157	63.0 %
PPS Years 6-11	5,498	6,725	81.8 %

(*) "Teaching" defined as any hospital reporting residents and receiving GME payments on the Medicare cost report.

There are 1,313 unique teaching hospitals identified by the HCRIS files for the PPS 6-11 period. Of these, 91% have IRIS data for at least one of the six possible years. Of unique hospitals with any IRIS data, 60% are missing IRIS files for at least one of the six applicable years. Table 6.6 compares characteristics of teaching hospitals with ("reporting") and without ("non-reporting") usable IRIS data. Non-reporting hospitals tend to be smaller and have fewer total residents, but slightly higher Medicare utilization rates. Although the differences in each of these categories are statistically significant, when academic status is controlled for the differences are only significant among minor

teaching hospitals. No patterns are evident with respect to non-reporting vs. reporting hospitals when analyzed by state, region or ownership status.

Table 6.6: Characteristics of Teaching Hospitals With and Without IRIS Data
(Base group is all teaching hospitals identified by HCRIS files, PPS Years 6 – 11)

	"Reporting": Observations w/ IRIS data (n=5,498)	"Non-Reporting": Observations w/out IRIS data (n=1,227)	t-statistic	P{difference in mean} = 0
# beds (mean)	318	286	- 5.29	< .00001
# resident FTEs (mean, from HCRIS)	69.0	59.7	- 2.72	.0065
Medicare utilization (mean, % days)	32.2 %	33.5 %	3.21	.0013
By Teaching Status: % that are —				
Minor Teaching	73.0 %	79.2 %		
Major Teaching – COTH only	15.5 %	15.8 %		
Major Teaching – AHC	11.5 %	5.0 %		

The IRIS data are used to conduct supplemental analyses that examine expansion in training for specific types of residents. Differences between reporting and non-reporting hospitals are not large, but they can still threaten the generalizability of any model results derived from the IRIS data. In order to test the external validity of models where the outcome variable has been computed from IRIS data, the Expansion Model is re-estimated using an outcome variable computed from HCRIS files, but on samples defined by IRIS availability. Differences in results across these versions of the Expansion Model are used to assess the possibility of selection bias in the sub-analyses of the Expansion Model that examine changes in resident subgroups as defined by IRIS data.

6.2.4 Conversion Model Sample

The study population for the Conversion Model consists of all hospitals that did not sponsor residents or receive Medicare GME dollars in their initial year of data in the HCRIS sample. In the first year of PPS there were 4,669 non-teaching hospitals. Between PPS 2 and PPS 11, another 178 non-teaching hospitals were added to the dataset, but there were also facilities that stopped providing GME or that closed, merged or changed ownership. Table 6.7 identifies the number of unique non-teaching hospitals and summarizes the effects of the exclusion criteria as defined earlier.

Table 6.7: Exclusions for Conversion Model Sample:

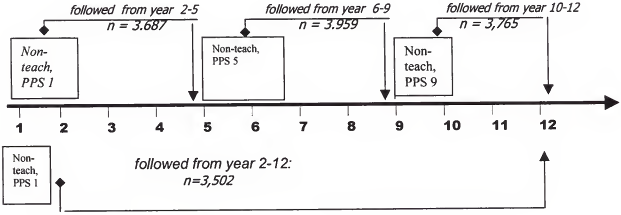
	Total
Single-Period Probability Sample:	
Non-Teaching Facilities in PPS 1:	4,669
Less: Initial Exclusion Criteria	–457
	4,389
Not Present Throughout Observation Period	–887
Remaining, Used in Descriptive Study	3,502
Missing PSF or Other non HCRIS data	–150
Remaining, Used in Multivariate Study	3,352
3-Period Probability Sample:	
Group 1	3,687
Group 2	3,959
Group 3	3,765
Total Sample	11,411
# Unique Hospitals in 3-Period Sample	4,167

The Conversion Model is estimated using two different sample definitions. First, a cohort of non-teaching facilities from PPS year 1 is followed over the full study period to determine which of its members converts to teaching hospital status. Of 4,389 non-teaching hospitals meeting initial inclusion criteria, 80% could be observed for all twelve

years. Another 3% were missing data in the PSF, but were still included in the descriptive study.

The length of the 12-year observation period introduces a possibility that changing hospital and/or external environmental characteristics could bias the model results. To test this, a second version of the model creates consecutive observation periods from hospitals identified at PPS 1, PPS 5 and PPS 9. Hospitals are assigned to an observation group according to their teaching status in these years. New non-teaching facilities opening between PPS 2 and PPS 9 are included in the sample, although facilities opening in PPS 10 or later are not. In the three-period model a hospital is identified as having converted to teaching status if it reports residents or receives GME reimbursement during the follow-up period *or* during the first year of the subsequent follow-up period, as depicted in the schematic in Figure 6.1, below:

Figure 6.1: Definition of Study Samples and Follow-up Periods for Conversion Model Samples



Hospitals converting to teaching status in one group are excluded from the subsequent groups, even if they stop sponsoring residents and then begin again at a later date. Hospitals that remain as non-teaching facilities through multiple periods, however, have observations in more than one group.

Chapter References

77. National Institute of Health. NIH Extramural Support to Domestic Medical Schools 1970-1996 http://silk.nih.gov/public/cbz2z0z.@.www.medrank.7096. 1998.

78. National Institute of Health. NIH Biomedical Research and Development Price Index, FY 1984-1995 http://www.nih.gov/grants/award/trends95. 1998.

79. American Medical Association. Accreditation Guide to Graduate Medical Education. Chicago, Ill: AMA; 1996.

7 Empirical Specification

7.1 Expansion Model

7.1.1 Estimating Equation

Growth in resident sponsorship among existing teaching hospitals is investigated using data from the subgroup of teaching hospitals, where the hospital is the unit of analysis and individual hospitals are observed over multiple years. Building on the general form of the Expansion Model as introduced in Equation 5.1, with the time lag (k) defined as one year, the estimating equation can be written as:

Equation 7.1:

$$\Delta FTE_{jt} = \alpha + \beta X_{j(t-1)} + \gamma(\Delta W)_{jt} + \lambda W'_{jt} + \phi Z_j + \delta(X_{j(t-1)}Z_j) + \{\varepsilon_{jt}+v_j\}$$

where:

> ΔFTE is defined as $(FTE_t - FTE_{(t-1)})$, where FTE is the number of residents claimed, in the main analysis or in sub-analyses by resident type.
>
> $\boldsymbol{X}$ represents the policy intervention variables of interest. They are defined as the marginal Medicare GME payments received for the last resident hired, measured from the cost reports of the preceding year. GME payments may be defined strictly as the indirect medical education component only, or as the sum of the indirect and direct components.
>
> $\Delta \boldsymbol{W}$ represents change in the inpatient capacity variables, which include total acute beds and critical care beds. Change is defined as $(\boldsymbol{W}_t - \boldsymbol{W}_{t-1})$.
>
> $\boldsymbol{W'}$ represents other time-varying covariates such as market or financial characteristics, which can be measured at period t or $(t-1)$. Included in this group is a lagged dependent variable, in the form of $FTE_{(t-1)}$
>
> $\boldsymbol{Z}$ represents the hospital characteristics that are expected to be fixed over time, including community size, academic status, ownership and a control for baseline hospital size at the beginning of the study period. $\boldsymbol{Z}$ may also include a time-trend

indicator. Interaction terms (the ***XZ***) are entered on those characteristics that are expected to act as effect modifiers in the relationship between Medicare GME payments and the outcome variable.

$\{\varepsilon_{jt}+v_j\}$, the two-part residual, indicates that the structure of the pooled cross-sectional data is expected to result in a component of the model error (v_j) which is related to the individual hospital and therefore correlated within cross-sectional units.

The study questions of interest are answered by the coefficients on the payment variable, $\beta_{\$IME}$. If the coefficients on the interaction terms are significant, then the study questions with respect to the indirect medical education payments are addressed by $\beta_{\$IME}$, conditional on the presence of characteristic Z (alternatively expressed as ($\beta_{\$IME}+\delta$).

The following specific hypotheses are tested:

- After controlling for increases in acute and critical care capacity, GME reimbursement will have a positive but small effect on growth in residency training.
  H_0: $\beta_{\$IME} = 0$
  H_A: $\beta_{\$IME} \neq 0$

  The portion of total growth in resident training that is explained by reimbursement incentives will be small, however, relative to the portion explained by changes in service delivery

- The strength of GME reimbursement incentives will vary by the academic affiliation status of the hospital. Reimbursement effects will be stronger among major community-based programs than among AHCs or minor affiliates.
  H_0: $\beta_{\$IME \mid \text{Other COTH}} = \beta_{\$IME \mid \text{AHC status}} = \beta_{\$IME \mid \text{Minor Teaching}}$
  H_A: $|\beta_{\$IME \mid \text{Other COTH}}| > |\beta_{\$IME \mid \text{AHC status}}| > |\beta_{\$IME \mid \text{Minor Teaching}}|$

- The strength of GME reimbursement incentives will vary by type of resident. Reimbursement effects will be stronger when the dependent variable excludes FTEs in surgical specialties, and stronger when the dependent variable is measured only for international medical graduates.
  H_0: $\beta_{\$IME \mid \text{initial cert}} = \beta_{\$IME \mid \text{non-surg}} = \beta_{\$IME \mid \text{primcare}} = \beta_{\$IME \mid \text{hosp based}}$
  H_A: $\beta_{\$IME \mid \text{initial cert}} \neq \beta_{\$IME \mid \text{non-surg}} \neq \beta_{\$IME \mid \text{primcare}} \neq \beta_{\$IME \mid \text{hosp based}}$

Also:
$H_A: |\beta_{\$IME \mid non\text{-}surg}| > |\beta_{\$IME \mid all\ fte}|$

H_0: $\beta_{\$IME \mid IMG\ only} = \beta_{\$IME \mid all\ fte}$
H_A: $|\beta_{\$IME \mid IME\ only}| > |\beta_{\$IME \mid all\ fte}|$

For the period when IRIS data are available, the main hypothesis may be tested twice — first using all residents in the designated groups, and once again using only first-year trainees ("PGY 1" residents). This restricts the model to new additions to the workforce, eliminating the effects of increased training time per resident.

7.1.2 Variable Specification

A complete description of the variables as constructed for the Expansion Model is included as Table 7.1. The specification chosen for the outcome variable is a value that is derived from the IME payment amounts, representing the change in the number of residents claimed for IME reimbursement from one PPS year to the next. Appendix 1.1 provides detailed background on alternative methods that were investigated for deriving resident FTEs from cost report or other HCFA data. The Medicare payment variables are deflated using the PPS Input Price index (1992 base), and scaled to units of $1,000. Appendix 1.2 provides the formulas used in computing marginal payment amounts. Appendix 1.3 describes the calculation of the variables designed to capture market factors. Appendix 1.4 describes techniques employed to deal with missing, extreme or inconsistent values in other independent variables.

Table 7.1: Expansion Model Variable Listing

	Source	Data Type	Definitions, Adjust's, Transformations
Dependent Variable:			
Main Analysis: Year-to-year change in resident FTE claimed for IME adjustment	HCRIS	Continuous	FTE_t - $FTE_{(t-1)}$
Sub-analyses (PPS 6-11 only) – Average annual:			
Δ PGY1 FTEs	IRIS	Continuous	[$FTE_{last\ yr}$ – $FTE_{first\ yr}$] / # yrs in period
Δ initial certification FTEs	IRIS	Continuous	[$FTE_{last\ yr}$ – $FTE_{first\ yr}$] / # yrs in period
Δ non-surgical FTEs	IRIS	Continuous	[$FTE_{last\ yr}$ – $FTE_{first\ yr}$] / # yrs in period
Δ primary care FTEs	IRIS	Continuous	[$FTE_{last\ yr}$ – $FTE_{first\ yr}$] / # yrs in period
Δ hospital-based FTEs	IRIS	Continuous	[$FTE_{last\ yr}$ – $FTE_{first\ yr}$] / # yrs in period
Δ IMG FTEs	IRIS	Continuous	[$FTE_{last\ yr}$ – $FTE_{first\ yr}$] / # yrs in period
Payment Policy Variables:			
Lagged marginal IME pmts received	HCRIS	Continuous	Per 1,000 1992 dollars
Or:			
Lagged marginal GME (=IME+DME)	HCRIS	Continuous	Per 1,000 1992 dollars
Major Covariates:			
Related to Service Delivery:			
1-yr change in routine bed capacity	HCRIS	Continuous	[$\#beds_t$ - $\#beds_{t-1}$] / 10
1-yr change in critical care bed capacity	HCRIS	Continuous	[$\#beds_t$ - $\#beds_{t-1}$] / 10
Related to Mission:			
Disproportionate Share Index	PSF	Continuous	log-normalized: $\ln(\text{DSHindex}+0.0351)_t$
Academic Status: Minor, Major, AHC	AAMC/AHA	Categorical	Reference = minor teaching
Ownership: Non-profit, propr. or public	HCRIS	0/1	Reference = non-public
Level of medical school research $: none, low, medium, high	NIH	Categorical	In constant $; reference = none
Related to Location / Competition:			
Rural, Small Urban, Large Urban	HCFA/AHA	Categorical	Reference = rural or small urban
Competition: # hospitals <= 15 miles	From zip code	Categorical	Ref =Low (0-2); medium(3-10); high(>10)
Finance-related Covariates:			
State Medicaid GME available	GAO	0/1	Reference = no Medicaid GME
New York State (All-Payer GME available)	GAO	0/1	Reference = hospitals not in NY State
Total Hospital Margin, lagged	HCRIS	Continuous	$[(\text{net revenue-expenses})/\text{net revenue}]_{t-1}$
Other Control Variables:			
Lagged Dependent: Prior Year # FTE	HCRIS	Continuous	log-normalized: $\ln(\text{FTE} +0.660)_{t-1}$ (*)
Base-year # acute beds	HCRIS	Continuous	log-normalized: $\ln(\text{beds}+110.216)_{\text{at } t=1}$
Time trends (base yr. + pre/post phase-in)	HCRIS	0/1	Ref = PPS 2; PPS 3-5; PPS 6-12
Interaction Terms tested:			
Academic status x Marginal IME$		0/1 x contin.	
Public ownership x Marginal IME$		0/1 x contin.	
Time trends x Marginal IME$		0/1 x contin.	
NY State x Marginal IME$		0/1 x contin.	

(*) The constant term added before log-transformation is set to minimize the skewness in the distribution of the transformed variable.

Different versions of the policy payment variable were tested, constructed from the IME payments only, the DME payments only, and a summed variable, labeled "marginal GME payment per resident". As identified in Appendix 1.2, there are additional problems in the DME amounts recorded during the earlier years, which call into question many of the 0-values appearing in the data. The model is tested using the "IME only" and the summed GME variables (with very little difference in results), but does not use the IME and DME measures as separate variables.

Changes in routine and critical care bed capacity are the model covariates that capture the effects of changing patient service needs over time. They have been scaled to reflect unit changes of 10 beds. Total bed capacity at baseline (the first year of data contributing to the analysis) is also entered as a control variable. Other measures of patient service delivery changes, such as case mix index or the proportion of aged to total discharges, are not included as covariates because they are implicitly included in the model through the calculation of the IME payments per resident. IME payments are a non-linear function of a hospital's number of residents, its total beds, its base DRG payment rate and its average DRG weight (see Chapter 3, section 3.2.3). When expressed on a per-resident basis, IME payments also become a function of the proportion of Medicare to total discharges. Similarly, DME payments are a function of the historical cost per resident and the current period proportion of Medicare days to total days. Thus, when the payment variables are entered into the model as marginal IME or GME payments per resident, case mix index and Medicare utilization rates are already accounted for. The Expansion Model also includes a lagged dependent variable, specified as the natural log of the actual number of FTEs for that hospital from the

previous year. This is a standard control variable included when modeling a change value, but because the lagged number of resident FTEs is also part of the computation of the lagged IME payment, its presence alters the interpretation of the coefficient on the IME payment variable. β_{IME} is defined as the effect of a unit change in the IME payment variable holding all other covariates constant. Resident FTEs are explicitly controlled for; bed capacity is indirectly controlled for through the combination of baseline capacity and changes in routine and critical care beds. Thus, the source of change in the IME payment is restricted to changes in Medicare caseload and intensity, and β_{IME} reflects the effect of these on the outcome variable.

Trend indicators identify whether an observation is from PPS years 3 through 5 or from the post-PPS phase-in period after year 5. The reference year is PPS 2; it is the first year in which a change in resident FTEs can be calculated, and is separated from the rest of the period for two reasons. First, its change variables and lagged variables are derived from PPS 1 data, which were of poorer quality and were subject to more estimation and interpolation than those of subsequent years. Second, there is reason to believe that hospitals were adjusting to the new rules in the first year, in particular the unfamiliar rules regarding "approved" and "non-approved" teaching sites, so that more changes are expected in the first year than during subsequent periods. Additional time trend indicators separate the remaining period into PPS phase-in and post-PPS phase-in. This is based on an assumption that management responses to PPS incentives could be different during the period when their exposure to national DRG rates was limited. In addition, some modifications were required for the computation of both marginal IME

payments and the DSH index prior to PPS year 6. The pre- and post-PPS indicators help to control for increased bias due to measurement error.

Change variables and lagged variables are included in the model for both conceptual and statistical reasons. The conceptual justification for lagging the payment variable is discussed in Chapter 5. The statistical advantages relate to control of bias due to the potential endogeneity in the model as diagrammed in Figure 5.1. Endogenous variables occur when the direction of influence can run either way ($X \rightarrow Y$ or $Y \rightarrow X$) or when one of the X variables is itself a function of another X variable. A condition of least-squares estimation techniques is that the X variables are determined externally from the model. Violating this condition results in an error term that is correlated with other X variables, and yields parameter estimates that are both biased and inconsistent. In the Expansion Model the main sources for possible endogeneity lie with the potential for a hospital's teaching commitments to influence its bed capacity, rather than vice-versa, and with the arithmetic relationship between total bed capacity and IME payments. These two problems are addressed by differencing the dependent variable and lagging the payment variables.

Lagged versions of an endogenous independent variable can be considered exogenous only if there is no serial auto-correlation [80]. Durbin-Watson tests on individual hospital series', however, produce no evidence of serial auto-correlation in this data (see Chapter 9 section 9.1.2 for a more detailed discussion). The inclusion of a lagged dependent variable in the form of prior year actual number of FTEs is also a form of control for potential negative auto-correlation in ΔY. This form of panel data estimation is also known as a "conditional change model" [81] in that the effects of the X

on ΔY are conditioned on prior values of Y, controlling for a natural regression-to-the-mean tendency in Y.

Table 7.1 indicates that several independent variables have been log-normalized to correct highly skewed distributions. The constants that were added prior to taking their natural log (identified in the fourth column of the table, when applicable) were identified by the statistical package as the value that minimizes the skewness of distribution of the transformed variable.

7.1.3 Statistical Issues in Panel Data Estimation

The Expansion Model is analyzed using a generalized estimating equation method (GEE), assuming continuous y with approximately normal distribution and explicitly modeling an error term in which there is a fixed correlation between any pair of errors within the hospital unit. Huber-White variance estimators provide control for possible additional cross-panel heteroscedasticity. Although this is not the most common method employed for analysis of cross-sectional time series, several alternative approaches were considered and rejected in favor of this method, for a variety of reasons as discussed below.

In the two-component error term appearing in Equation 7.1, ε_{jt} represents the random portion of the model residual which is assumed to meet OLS assumptions (mean equal to zero, constant variance of σ_ε^2, uncorrelated with the X's and uncorrelated with itself). The component ν_j, however, is a unit-specific residual that measures the contribution of the cross-sectional unit (in this case, hospital) to the model residual. If the hospital-specific effect is assumed to be fixed within hospital over time, it can be modeled as a fixed contribution to the intercept term. If ν_j is constant within j, then

"y_{jt}=$\alpha + \beta\mathbf{X}_{jt} + \{\varepsilon_{jt} + \nu_j\}$" is equivalent to "$y_{jt}$= $(\alpha+\nu_j) + \beta\mathbf{X}_{jt} + \varepsilon_{jt}$" which can be written as "y_{jt}= $\alpha_j + \beta\mathbf{X}_{jt} + \varepsilon_{jt}$". Valid OLS parameter estimates can be obtained by incorporating 0/1 variables for each cross-sectional unit into the model, thereby generating a series of hospital-specific intercept terms. This is known as the "fixed effects technique". Since the addition of hospital-specific dummy variables controls for all cross-sectional variation, the slope parameter estimates are derived solely from variation within each unit — that is, between the individual observations and their hospital-specific means. For this reason they are sometimes referred to as the "within" estimators [82].

In a fixed effects analysis, the addition of hospital-specific dummy variables requires that the estimation eliminate any other unit-specific, time-invariant measures because they become perfectly collinear with the hospital indicators. Although the model continues to control for characteristics captured by the dropped variables, their measured effects cannot be separated from all other fixed effects of the hospital indicators. For the Expansion Model this would effectively eliminate measures of the effects of academic status, ownership and location from the model, although it is still possible to retain their second-order interaction terms. A second and more serious problem with the fixed effects approach in the Expansion Model is the fact that the dependent variable is already a first-difference measure. The coefficients modeling within-hospital temporal effects of the $\boldsymbol{X}$ on a change variable no longer directly address the study question and their interpretation is problematic.

Alternatively, the residual ν_j can be modeled as a hospital-specific random variable. With the introduction of another random variable to the linear model, the variance-covariance matrix of the error term is no longer equal to σ^2I (where I is an Identity

matrix) but $\sigma^2\Sigma$, where Σ is an unknown, positive definite matrix. The notation implies the presence of group-wise heteroscedasticity and/or auto-correlation. Under these circumstances, OLS on an otherwise fully specified model produces parameter estimates that are unbiased but not most efficient (that is, not possessing the least variance). General linear modeling (GLM) is needed to obtain minimum-variance linear estimates. The particular form of GLM that is most appropriate depends upon the assumptions made about the structure of the correlation in the error term, or more specifically, of $\sigma^2\Sigma$.

If observations within hospital unit are assumed to be correlated, and the correlation is not identified as a function of some other factor (most commonly, time) then the equation may be estimated using a random effects generalized least squares (GLS) technique. In general terms, GLS obtains best linear estimates by transforming y and $\boldsymbol{X}$ into variables $\boldsymbol{y}^*$ and $\boldsymbol{X}^*$ that satisfy standard OLS assumptions, then running OLS on the transformed values. The transformation function is derived from prior knowledge of or assumptions about the source of the heteroscedasticity and the structure of the variance-covariance matrix. The random effects technique requires an assumption that the errors are correlated within hospitals units, and that the correlation can be represented by the same random variable across any given pair of within-unit observations. The GLS transformation factor is derived from an estimate of the variance of the hospital-specific component of the error term ($\hat{\sigma}_v{}^2$). The estimate is derived in part from the difference between the squared error term from a fixed effects (or "within unit" estimation, as described above) and that from a secondary OLS estimation on mean values of $\overline{y}_{j.}$ and $\overline{X}_{j.}$ (or "between unit" estimation). Random effects techniques are commonly used in

cross-sectional time series analyses, where the data contain a large number of cross-sectional units observed over a limited number of time periods.

As described by Judge *et al*[83], however, with some types of data the formula for estimating $\hat{\sigma}_v{}^2$ yields a negative number and random effects cannot be used. The Expansion Model sample encountered this problem, probably due to the change-value specification of the dependent variable that produced a large number of within-unit negative and positive values. As an alternative, therefore, the Expansion Model uses GEE with restricting assumptions on the distribution of both y_{jt} and ε_{jt} that are similar to the assumptions included in a random effects model.

The most general representation of the GEE model is

Equation 7.2: $$g(E(y_{jt})) = \boldsymbol{X}_{jt}\,\boldsymbol{\beta} + \varepsilon_{jt}$$

where y is assumed distributed by some function F and a correlation structure for the ε_{jt} must be explicitly modeled. If y is continuous with an approximate normal distribution and errors are assumed to be independent, for example, GEE generates results equivalent to OLS regression with robust standard errors. Imposing a structure of fixed correlation within hospital unit generates results that are very similar to those generated by the random effects method. Although it is also possible to model an auto-regressive error structure (e.g. correlation that decreases over time), this option is not explored for the Expansion Model because previous tests of the data show no evidence of serial auto-correlation.

GEE methods are more commonly employed in analyzing data from cluster samples than from repeat observation samples such as the one used for the Expansion Model. If the number of clusters (in this case, hospital units) is large, the GEE method

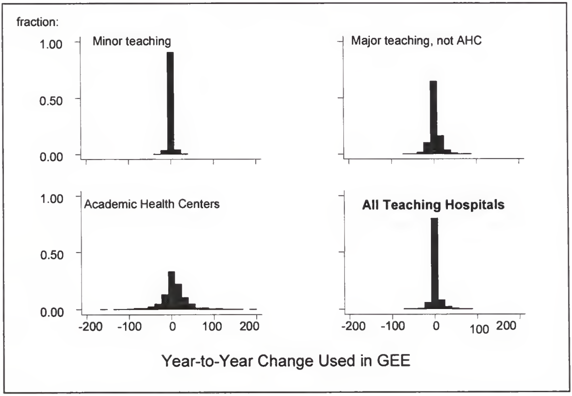
produces results that are very similar to the more commonly used error components methods. GEE is said to produce consistent estimates of the regression parameters and their variances even when the constraining assumptions regarding the structure of the within-cluster error correlation are incorrect, provided the original equation is properly specified [84]. If an error structure is imposed that is not one of independence, however, then estimation is accomplished using iterative variance re-weighted least squares regression. The choice of imposed correlation structure will alter the variance-covariance matrix (and thus the weights) of each iteration, thereby also altering the GLS coefficients [85].

Like the random effects method, GEE allows for correlation within unit but assumes that errors from one hospital unit are not correlated with errors from another. In other words, there should be no heteroscedasticity between the cross-sections. An advantage of GEE over random effects, however, is that Huber-White estimators of variance can be added to GEE models to make the standard errors "robust" to possible mis-specification with respect to cross-hospital heteroscedasticity.

The Expansion Model's outcome variable of year-to-year change in resident FTEs is inherently noisy, with a large proportion of observations showing small positive or negative changes even though the long-term trend is positive. Figure 7.1 shows the distribution of the change variable as used in the GEE model, over all twelve years of data, for hospitals grouped by teaching status. Within some unique hospitals, year-to-year change can be large, followed by a similarly large change of opposite sign. Most of the observations at the extremes of the distributions plotted in Figure 7.1 derive from this type of within-hospital pattern, and may represent reporting errors. To the extent that the

differences are offsetting within hospital unit, they would not bias the parameter estimates. Their effect on the model should be limited to an increase the model variance and a widening of the standard errors of the parameter estimates.

Figure 7.1: Distribution of Dependent Variable for GEE Specification, by Type of Teaching Hospital



The presence of within-unit swings in the outcome variable does, however, raise the question of whether single year variation is the appropriate measurement unit for change in residency sponsorship. To address this I test a second model, which uses OLS to examine average changes over a longer time frame, as a function of the hospital characteristics at the beginning of that time. Although this approach ignores much of the information provided by the multiple observations within hospital, it has the advantages

of eliminating the problem of panel correlation and allowing for simpler estimation techniques. By eliminating the noise from within-unit year-to-year variation, the simpler model also makes it possible to gain a better sense of the fit of the mean function, that is, the ability of the functional form and the model covariates to jointly explain the long-term trends in residency program expansion. Observations are divided into those from PPS years 2 – 5 and those from PPS years 6 – 12. Two sets of Y variables are calculated as $(FTE_{@\,t=5} - FTE_{@\,t=2})/3$, and $(FTE_{@\,t=12} - FTE_{@\,t=6})/6$. The ΔW variables are similarly computed. Two separate OLS regressions are conducted, on sub-samples using only the observations from PPS 2 and from PPS 6.

Secondary analyses of the IRIS data from the period PPS year 6 through PPS year 11 are handled in a similar manner as the analysis from the main Expansion Model. OLS on average annual change, however, is modeled over only one period.

7.2 Conversion Model

7.2.1 Estimating Equations

The Conversion Model follows a cohort of non-teaching hospitals over a defined observation period to identify which of them converts to teaching status. The purpose is to determine whether the probability of conversion is associated with the size of potential Medicare reimbursement gains, after controlling for hospital characteristics observed at the baseline of the study period. The dependent variable for conversion is dichotomous, coded as "1" if the hospital reports any residents on its cost report during the observation period and "0" if it does not. The effect of the independent variables on the probability of conversion is modeled using logistic regression, a maximum likelihood estimation

technique that assumes a logistic distribution of the error term. The dependent variable is restated as the natural log of the odds of the outcome event, or "logit". Expressed in its logit form, the estimating equation for the probability model on the single observation period is:

Equation 7.3:

$$ln\left\{\frac{P(conversion)}{1-P(conversion)}\right\} = logit_{convert} = \alpha + \beta IME^{*} + \gamma \boldsymbol{W} + \phi \boldsymbol{Z} + \delta IME^{*}\boldsymbol{Z} + \varepsilon$$

where:

IME* represents the potential Medicare IME payments available per new resident hired;

W is the vector of hospital operating characteristics;

Z is the vector of hospital environmental characteristics, and ***IME*Z*** represents selected interaction terms.

Two versions of the probability model are tested. The first includes data only on hospitals appearing in PPS 1. It contains one observation per non-teaching hospital and obtains all values for the covariates from the observations in PPS 1. The elapsed time between the independent variable measurement and conversion can therefore range from one to eleven years. For a hospital with a given covariate pattern, model results will predict the probability of converting to teaching status within the first twelve years of PPS.

The second version divides the study sample into three observation periods, as described Chapter 6.2.4. The study sample for this version contains multiple observations per hospital if the hospital remains non-teaching for more than one

observation period. The maximum number of observations per unit is three, if a hospital appears in all twelve years of data and never converts. Independent variables are computed at base year for each observation group; thus the maximum elapsed time between the independent variable measurement and conversion is only four years. Results of the three-period version of the model therefore predict the probability of converting to teaching status within the next four years. The main advantage of the three-period model is that the independent variables are more likely to reflect the hospital operating environment that is appropriate to the period in which the teaching decision is made. (Because conversion to teaching status is a relatively rare event in this data — about 1% or 30–35 per year — some grouping of the years is necessary in order to have sufficient outcome events to accommodate the model.) For the three-period model, the only alteration needed to Equation 7.3 is the addition of time-trend indicators and their respective interaction terms. Time trends, in the form of indicator variables for membership in the first, second or third group, enable the second version to provide control for any secular trends that may have affected the hospital's teaching decisions. Use of robust standard errors with correction for clustering by hospital provides control for the lack of independence from repeat measures on hospitals appearing in multiple observational periods.

The study question of interest is answered by the coefficient on the payment variable, β_{IME^*} (or β_{IME^*} plus coefficients on interaction terms, where applicable). The specific hypothesis tested is:

- Potential IME reimbursement gains will have a positive but small effect on the probability of converting from non-teaching to teaching status, after controlling for characteristics of hospital operations and the external environment.

In the single-period version the null and alternative hypotheses are represented by:

H_0: $\beta_{IME*} = 0$

H_A: $\beta_{IME*} \neq 0$

In the three-period version they become:

H_0: $\beta_{IME*\,|\,PPS\ 1\text{-}4} = \beta_{IME*\,|\,PPS\ 5\text{-}8} = \beta_{IME*\,|\,PPS\ 9\text{-}12} = 0$

H_A: $\beta_{IME*\,|\,PPS\ 1\text{-}4} \neq 0$

$\beta_{IME*\,|\,PPS\ 5\text{-}8} \neq 0$

$\beta_{IME*\,|\,PPS\ 9\text{-}12} \neq 0$

When the coefficients are exponentiated, $\exp(\beta)$ and $\exp(\beta+\delta)$ are odds ratios representing the proportional effect of a one-unit change in the payment variable on the likelihood of converting to teaching status. The predicted probability of conversion for a hospital with a particular set of covariates is given by $[\exp(\Sigma X\beta) / (1+ \exp(\Sigma\text{-}X\beta))]$. The absolute effect of a unit change in the payment variable is best portrayed by a series of computations that are conditioned on a set of covariate values that are relevant to the sample.

7.2.2 Variable Specification

A complete description of the variables as constructed for the Conversion Model is included in Table 7.2. Background on variable construction and data editing is included in the material in Appendix 1. The payment policy variable of interest in the Conversion Model is a measure of potential IME payments receivable for a given hospital. It must be calculated based on the hospital's size, its initial DRG payment rate, its average case mix, and its Medicare caseload, all as experienced in the base year of the observation period. For purposes of this calculation the number of residents in the newly converted facility is assumed to be three FTEs, which is approximately the median

number of FTEs reported by new teaching hospitals. The DME payment variable is not a factor in the Conversion Model since in the case of newly designated teaching hospitals there is no historical average cost per resident (ACPR) and prospective DME payment is based on regional averages.

The Conversion Model is somewhat more restricted that the Expansion Model in its choice of independent variables because of the limited number of outcome events. Total Operating Margin does not appear in the model because its instability over time makes it a poor predictor as a base year characteristic. Acute care capacity is expressed as a three-level ordinal variable representing small, medium and large community hospitals. Indigent care obligation is also measured using a three-level version of the same disproportionate share index that was computed for the Expansion Model.

To control for the level of hospital sophistication, cost and service utilization data from the HCRIS files were used to identify the presence of a critical care unit, the availability of maternity services, and the proportion of operating room costs to total ancillary costs. The relative importance of surgical caseload within the hospital is used here as a proxy for the sophistication of the professional medical community, and as a means to separate small recuperative, or "cottage" hospitals, from acute medical-surgical facilities.

Table 7.2: Conversion Model Variable Listing

	Source	Data Type	Definitions, Adjust's & Transformations
Dependent Variable:			
For single observation period, 12 years:	HCRIS	0/1	1 if converted any time during PPS 2-12
For three observations periods:	HCRIS	0/1	1 if converted any time during that period
Payment Policy Variables:			
Potential IME$ Receivable per Resident	HCRIS	Continuous	Per 1,000 1992 dollars
Major Covariates:			
Related to Service Delivery			
Hospital Size (# acute care beds)	HCRIS	Categorical	1= reference(<=50); 2 (51-150); 3=>150
O.R. costs as % All Ancillary	HCRIS	Ordinal (1-5)	1 (=<5%) through 5 (>30%)
Related to Mission			
Indigent care levels(DSH Index)	PSF	Categorical	1= reference(<=15%) 2 (15-30%) 3 (>30%)
Ownership: Proprietary	HCRIS	0/1	
Public		0/1	
(Reference= Non-profit)			
Related to Market			
Location & Competition:	From zip codes		Defined as number of Medicare-participating facilities (non-VA) within 15 mile radius
Rural, no competitors (reference)			
Rural, 1 or more competitors		0/1	
Urban, no competitors		0/1	
Urban, 1-5 competitors		0/1	
Urban, >5 competitors		0/1	
Distance to nearest COTH facility	From zip	0/1	1= location with 15 miles of COTH member
Patient Care Physician/100,000 pop	ARF	Categorical	1= reference(<=50); 2 (51-150); 3 (>150)
Time Trends			
Group 1: PPS Yr 1 (reference)	HCRIS		
Group 2: PPS Yr 5	HCRIS	0/1	
Group 3: PPS Yr 9	HCRIS	0/1	
Interactions tested:			
Location x $IME*		0/1 x contin.	
Ownership x $IME*		0/1 x contin.	
Time Trends x $IME*		0/1 x contin.	

In order to conserve degrees of freedom, an index was constructed that combined scores from an ordinal version of the operating room cost proportion with 0/1 values for critical care and maternity services, weighted by coefficients from a restricted regression of these three variables on the probability of conversion. Although all three components of the index were significant predictors of conversion in the restricted model, the index

performed no better than the operating room cost variable by itself in the fully specified Conversion Model. The final model therefore retains only an ordinal specification of the proportion of surgical to total ancillary costs.

Variables related to location and competition are expressed categorically. The ratio of patient-care physicians to 100,000 population was computed as a continuous variable at the county level; hospitals were then identified as belonging to communities with low, medium and high physician supply, using the cutpoints identified in Table 7.2. A variable measuring distance from the nearest major teaching hospital (defined as any non-federal COTH member) has also been computed. This variable was reduced to a 0/1 indicator for hospitals within 15 miles of a major teaching facility after exploratory analysis indicated that the likelihood of converting was much greater for that group, and that remaining categories beyond the 15-mile radius were not significantly different from each other.

The effects of location were originally represented by categorical variables indicating rural, small urban and large (population > 1 million) urban communities based on MSA designation. A continuous measure of the number of competitors, based on the number of Medicare-participating facilities within 15 miles, was reduced to three levels of competition using the cutpoints as identified in Table 7.2. Community size and market variables suffer from a high degree of collinearity, however, and they produced coefficients that were unstable when relatively minor changes were made in the model specification and/or analysis sample. To address this problem, a set of five dichotomous variables was constructed representing rural hospitals with no competition, rural hospitals with any competition, urban hospitals with no competition, urban hospitals with 2–5

competitors, and urban hospitals with greater than five competitors. This new set of variables is used in place of separate community size and competition measures.

Interaction terms were constructed on the potential IME payment variable by ownership, by DSH category, by location and by observation period. These were tested simultaneously, and eliminated from the model if their parameter estimates were not significant at a $p < .05$ level.

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8 Descriptive Study Results

8.1 Expansion Model Study Samples

8.1.1 Characteristics of the Teaching Hospitals

Teaching hospital characteristics stayed relatively constant over the twelve-year study period. Over 70% of hospitals in the Expansion Model sample were minor teaching facilities, either small community-based programs or affiliates of the major programs. Eleven percent of the teaching hospitals were academic medical centers (see Table 8.1). The teaching hospital sample as a whole is overwhelmingly urban (95.3%), and over one-half of the hospitals were located in metropolitan areas with populations greater than 1 million. Of these, over three fourths were competing with ten or more hospitals within a 15-mile radius. In the last year of the sample, 17% of teaching hospitals in large urban communities were competing with 50 or more hospitals within a 15-mile radius. The distribution of teaching facilities by city size and competition levels showed only minor changes over the study period.

Approximately two thirds of all facilities in the sample were disproportionate share providers and nearly half of these had high DSH index scores, indicating a high level of indigent care obligation. Among academic health centers, 94% were disproportionate share providers and two thirds of these had high DSH index scores. The proportion of proprietary-owned teaching facilities is small but increased over the study period from 3.8% to 7.6%. Proprietary-owned teaching hospitals are predominantly small, community-based programs.

Table 8.1: The Teaching Hospitals Sample —Institutional Characteristics as of PPS Year 12 (1994 – 1995)

	Number (N=1,043)	*% (100%)*
Academic Status		
Minor Teaching (not COTH members)	*770*	*73.8%*
Major teaching (COTH members, non-AHC)	*163*	*15.6%*
Academic Health Centers	*110*	*10.6%*
Community Size		
Rural (non-MSA)	*54*	*5.2%*
Urban, <100,000 population	*12*	*1.1%*
Urban, 100,000 - 249,999	*111*	*10.6%*
Urban, 250,000 – 999,999	*275*	*26.4%*
Urban, >= 1,000,000 population	*591*	*56.7%*
Ownership		
Private, non-profit	*817*	*78.3%*
Public	*147*	*14.1%*
Proprietary	*79*	*7.6%*
Disproportionate Share Index		
Low (index value <=.15)	*330*	*31.6%*
Medium (index value >.15 & <=.30)	*391*	*34.5%*
High (index value > .30)	*322*	*30.9%*
Competition (# hospitals within 15 miles)		
Low (<=2 competitors)	*187*	*17.9%*
Medium (3-10 competitors)	*375*	*36.0%*
High (>10 competitors)	*481*	*46.1%*
Research Commitment (NIH funding levels)		
None	*913*	*87.5%*
Low (<= $18 million)	*59*	*5.7%*
Medium ($18 - $70 million)	*55*	*5.3%*
High (> $70 million)	*16*	*1.5%*

The level of biomedical research obligations (as measured by NIH funding amounts at the associated medical schools) serves to differentiate mission within categories of academic status. The distribution of research activity is highly skewed, with only 13% of facilities identified as active research sites affiliated with university grantees. Of these, 85% were academic medical centers. Across the subset of research-affiliated sites there was substantial variation in the levels of funding at their associated

universities, with 50% falling into the relatively low funding group, 40% in the middle category and only 10% in the highest category.

Table 8.2 presents selected time trends within the analysis sample by summarizing key operating statistics at the beginning and end of the study period, for all facilities combined and within categories by academic status.

Table 8.2: Summary Hospital Operating Statistics at the Beginning and End of Study Period, by Academic Status *(arithmetic means, by group)*

		All Facilities in Sample	*Minor Teaching Facilities*	*Major Teaching Facilities, not AHC*	*Academic Health Centers*
Number of Facilities	*Year 1*	*842*	*615*	*129*	*98*
	Year 12	*1043*	*770*	*163*	*110*
	% Δ	*+24%*	*+25%*	*+26%*	*+12%*
Routine Care Beds	*Year 1*	*325*	*276*	*463*	*451*
	Year 12	*259*	*211*	*380*	*414*
	% Δ	*−20%*	*−24%*	*−18%*	*−8%*
Critical Care Beds	*Year 1*	*33*	*25*	*50*	*60*
	Year 12	*41*	*29*	*65*	*94*
	% Δ	*+24%*	*+16%*	*+30%*	*+57%*
% Medicare Utilization	*Year 1*	*31%*	*32%*	*30%*	*22%*
	Year 12	*35%*	*37%*	*31%*	*26%*
	% Δ	*+13%*	*+16%*	*+3%*	*+18%*
Total Operating Margin	*Year 1*	*7.9%*	*7.8%*	*8.9%*	*6.9%*
	Year 12	*4.2%*	*4.2%*	*4.4%*	*3.8%*
	% Δ	*−47%*	*−46%*	*−51%*	*−45%*
Resident / Bed Ratio	*Year 1*	*.1491*	*.0855*	*.2098*	*.4687*
	Year 12	*.1943*	*.1065*	*.3192*	*.6234*
	% Δ	*+30%*	*+25%*	*+52%*	*+33%*

8.1.2 Trends in Sponsorship, 1984 – 1995

The total number of resident FTEs that were claimed for IME reimbursement purposes by study sample hospitals increased by more than 26,000 between PPS year 1 and PPS year 12. The average increase in total IME FTEs was 4.6% per year. As can be seen in Table 8.3, much of the growth in the earlier part of the study period is attributable to increased numbers of Medicare-approved teaching hospitals. In the earlier part of the study period some of this growth may be reporting artifact. "New" residents may have already been in place in non-approved sites prior to PPS implementation; as hospitals were motivated by GME regulations to apply for approved teaching status, residents would appear as "new" to the Medicare program.

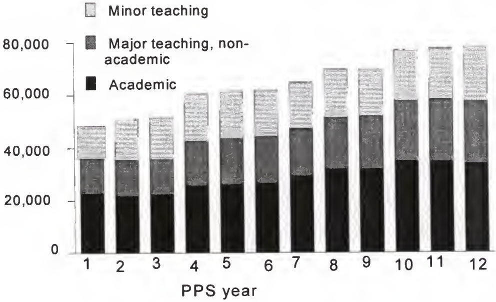
Table 8.3: Growth in Total Residents Claimed for IME Payment Adjustments

	# Hospitals in Study Sample	*% change*	*Mean # Resident FTEs*	*% change*	*Total # Resident FTEs*	*% change*
All Teaching Hospitals						
Year 1	*842*		*61.3*		*51,570*	
Year 6	*983*		*62.0*		*60,970*	
Year 12	*1043*	*+23.9%*	*73.9*	*+20.6%*	*77,055*	*+51.0%*
Minor Teaching Only:						
Year 1	*615*		*25.0*		*15,388*	
Year 6	*719*		*23.3*		*16,762*	
Year 12	*770*	*+25.2%*	*25.7*	*+ 2.4%*	*19,779*	*+28.5%*
Major Teaching, non-AHC:						
Year 1	*129*		*104.4*		*13,470*	
Year 6	*158*		*111.6*		*17,626*	
Year 12	*163*	*+26.4%*	*143.0*	*+37.0%*	*23,313*	*+73.1%*
Academic Health Centers:						
Year 1	*98*		*231.8*		*22,712*	
Year 6	*106*		*250.5*		*26,552*	
Year 12	*110*	*+12.2%*	*308.8*	*+33.2%*	*33,968*	*+49.6%*

Changes over time in the number of facilities may also be distorted by the effects of the exclusion criteria, since poorer data quality in the earlier reporting years resulted in a larger number of excluded observations. Averages within groups, however, should not be affected by this problem.

Nearly all of the increase in resident FTEs among minor teaching programs occurred as a result of establishing new training sites; the average number of residents per site in this group increased only from 25.1 to 25.7 over the twelve years. The average number of residents claimed by academic medical centers grew from 231.7 to 308.8. Nevertheless the portion of total residents based in academic health centers remained at 44% from the beginning to the end of the study period. Figure 8.1 charts the total number of residents claimed each year for IME payment adjustment purposes, grouped by academic status of the clinical site that received the Medicare payments.

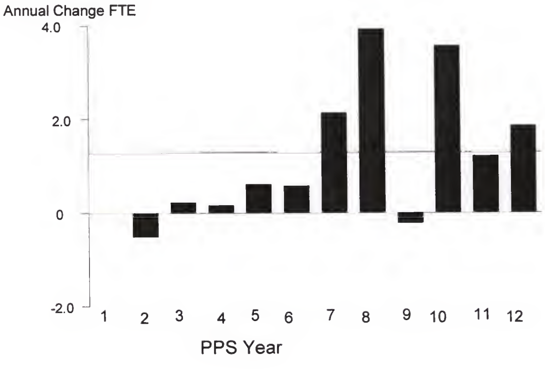
Figure 8.1: Total Residents Claimed for Indirect Medical Education Payments PPS 1 through PPS 12, by Academic Status of the Hospital



Non-academic major teaching sites grew both in numbers (from 129 to 163) and in average program size (104.4 to 143.0), resulting in a total increase in their resident FTEs of over 73%. Although this causes some increase in their share of total trainees, Figure 8.1 reveals no substantive structural changes over the study period in the distribution of trainees by the status of their hospital rotation site.

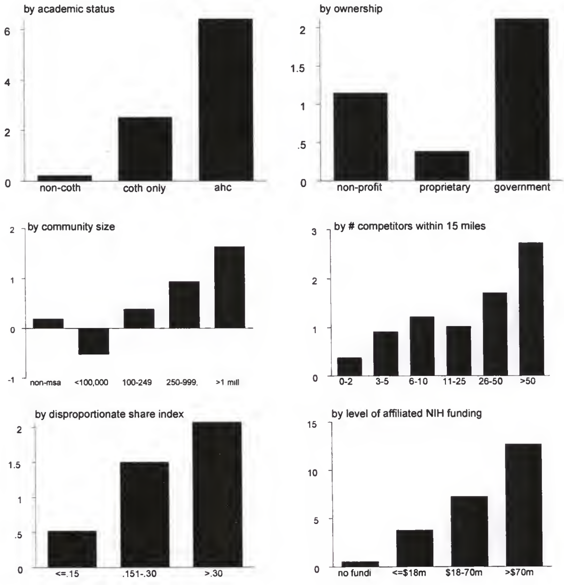
Most of the growth in size of existing programs occurred after 1988 (PPS 5) when the PPS phase-in period ended. Figure 8.2 depicts the annual increase in FTEs per site, by PPS year and by type of teaching facility. Across all sample hospitals, the site-based year-to-year change in resident FTEs averaged 0.16 during the phase-in, but 1.86 afterward. The average annual change for the 12-year period was only 1.29 FTEs.

Figure 8.2: Year-to-Year Change in Resident FTEs Claimed for IME Payment: Averages by Site, by PPS Year



Larger programs are naturally more likely to experience larger year-to-year changes. The site-specific changes vary widely not only by hospital size, but also by type of teaching hospital. This can be seen from the graphics presented in Figure 8.3.

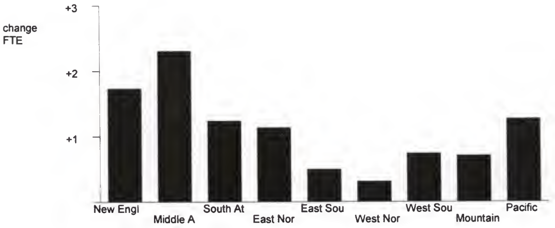
Figure 8.3: Patterns in Program Expansion: Average Annual Change in Resident FTEs, by Selected Hospital Characteristics



The variable charted for Figure 8.3 is the average annual change in FTEs, which is a constant within unique facility (computed by subtracting FTEs as of the hospital's first year of data from FTEs in its last year of data, and dividing by the number of years between the two observations). The individual facility averages are then summarized across hospital groups.

There are also pronounced regional differences in program expansion, as shown in Figure 8.4. The Middle Atlantic and New England regions, home to the largest academic centers and a majority of the most prestigious research centers, saw the largest increases in sponsorship.

Figure 8.4: Average Annual Change in Resident FTEs, by Region



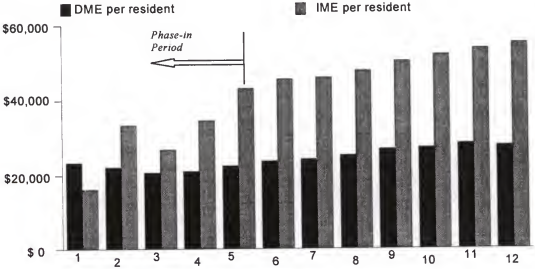
Patterns of program expansion in the Middle Atlantic region are dominated by teaching activities in New York State. By the last year of the study period, New York was home to 10% of the teaching hospitals in the sample, but sponsored 19% of all residents claimed for IME payment. The average annual increase in FTEs for all NY teaching sites was 4.42, compared to 1.05 in other states. Among academic health centers, sponsorship

increased by an average of 14.8 FTEs per year in New York, compared with 5.7 FTEs elsewhere.

8.1.3 Trends in GME Payments, 1984 - 1995

Real indirect medical education payments per resident show a steady increase after the PPS phase-in period ended, which is a reflection of increasing relative Medicare utilization and increasing case mix index values. Through PPS 5, the IME payments show an uneven year-to-year pattern that reflects a combination of the increasing federal/hospital-specific blends in effect during the phase-in, and mandated reductions in the IME payment formulas. Between PPS years 6 and 12, however, real marginal IME payments per resident grew by 21%, from \$45,226 to \$55,213.

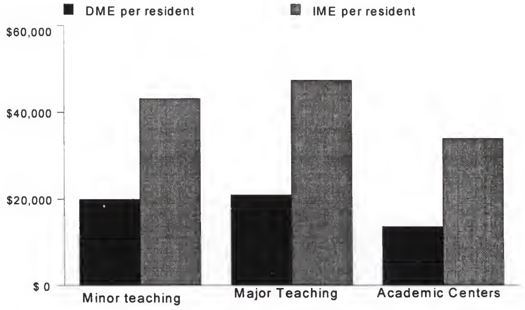
Figure 8.5: Trends in Real Direct and Indirect Medical Education Payments/Resident FTE, Averaged Across Hospitals, by PPS Year
(marginal payment received for last resident hired, in '000s of 1992 dollars)



DME payments were not subject to the phase-in. For the first five years under PPS they were paid as part of the combined capital and education cost "pass-through", and not every HCRIS record identified the DME amounts received separately from the capital amounts. In Figure 8.5 the average DME payments per resident are computed based on the subset of hospitals which reported at least some DME reimbursement, in order to be comparable to the mean values computed in later years.

Both types of GME payments vary widely across hospitals. In PPS 12 the mean IME payment received for the last resident hired was approximately \$55,000, but 10% of the sample received less than \$21,000 and 10% received more than \$85,000. The mean Direct GME payment was just under \$27,000 per FTE, but 1% of teaching hospitals were not eligible for any DME (because they were affiliates who were not incurring any direct costs) and 1% received over \$78,000. Within each of the twelve years there are consistent differences in marginal per-resident payments received across hospitals grouped by academic status. Figure 8.6 shows that academic health centers received, on average, the smallest amounts per resident. The amounts are highly sensitive to the proportion of Medicare discharges, however, and due to their larger indigent care and Medicaid obligations, academic centers tend to have proportionally fewer Medicare patients (refer to Table 8.3).

Figure 8.6: Real Direct and Indirect Medical Education Payments per Resident FTE, By Academic Status (*marginal payment received for last resident hired, over '000s of 1992 dollars, averaged over study period)*



Across the sample as a whole, there is no consistent bivariate relationship between amounts received per resident and increases in resident FTEs sponsored. In Table 8.4, the IME and DME per-resident amounts have been added together and categorized into five levels. Hospitals are grouped by the level in which they fell as of PPS 12, although the statistics that are presented have been computed over all observations in the study period. The largest increases residency sponsorship appear to have occurred in hospitals in the middle GME payment categories.

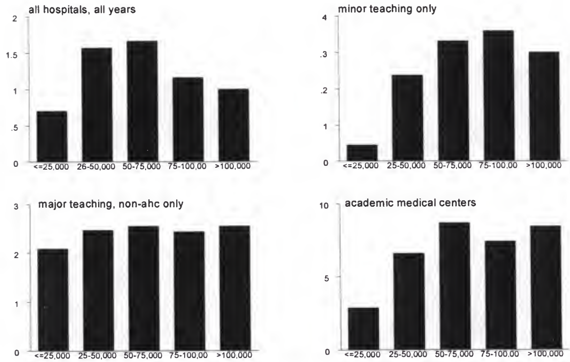
Table 8.4: Average Annual Increase in Resident FTEs, by Real Total GME Payments per Resident, Grouped as of PPS Year 12
(Total GME is the sum of marginal IME payment plus DME payment)

Total GME per Resident	*Distribution: Number Hospitals (as of year 12)*	*%*	*Average Annual Change in Resident FTE s claimed*
<= $25,000	*57*	*5.5%*	*+ 1.02*
$25,001 - $50,000	*136*	*13.0%*	*+ 2.07*
$50,001 - $75,000	*274*	*26.2%*	*+ 2.46*
$75,001 - $100,000	*275*	*26.4%*	*+ 1.15*
> $100,000	*301*	*28.9%*	*+ 1.15*
Total	*1043*	*100.0%*	*+ 1.61 (*)*

(*) Note that this Average Annual Change appearing on the Total line differs from the average increase for the sample as a whole computed for Figure 8.2, because it is computed across only those facilities present in PPS year 12.

A stronger pattern emerges between reimbursement gain and sponsorship among selected hospital subgroups, as shown in the charts in Figure 8.7. For this presentation, sponsorship changes are computed on the same payment groups as appear in Table 8.4, but they include all observations from all years (effectively weighting the contributions of hospitals by the number of years they appear in the sample). The hospitals are stratified by academic status. The results suggest that payment rates may affect sponsorship decisions within minor teaching hospitals and within the academic medical center group.

Figure 8.7: Average Annual Increase in Resident FTEs, by Real Total GME Payments per Resident, by Hospital Academic Status



8.1.4 Sponsorship by Type of Resident , 1989 – 1994

8.1.4.1 Consistency of Data, IRIS and HCRIS files

Data from the Interns & Residents Information System (IRIS) provide an alternative source for computing the number of resident FTEs sponsored by approved teaching hospitals. Although available only for the period PPS 6 through 11, the data are much richer and allow for separate analyses by type of resident and specialty training. The IRIS records have been summarized at the individual hospital level, but they are not available for all study hospitals even within the applicable years. In addition, IRIS data

are compiled for use by HCFA as a cost report audit tool, but they are not updated for audit corrections. Some differences between the number of full time equivalents as computed from IRIS records and the number claimed for payment on final cost reports are therefore expected.

Among those facilities for which both data sources are present, the measurement differences in the count of total FTEs are small. Correlation coefficients within each year are all over 0.97. Year-to-year change in FTEs, however, is an inherently less stable measure. The variance is greater (relative to the mean) and the change variable is more vulnerable to FTE measurement differences. Comparisons for both the total and the change variables from the two sources are provided in Table 8.5

Table 8.5(a): Comparison of *TOTAL* Resident FTEs Claimed for Medicare Payments on HCRIS and IRIS Files — Hospital Averages, by Year

Year	*N*	*From HCRIS files (mean)*	*From IRIS Files (mean)*	*% difference*	*Correlation Coefficient*
PPS 6	*813*	*64.92*	*65.59*	*+ 1.0%*	*.98*
PPS 7	*980*	*65.51*	*66.16*	*+ 1.0%*	*.97*
PPS 8	*990*	*69.64*	*66.05*	*– 5.2%*	*.97*
PPS 9	*889*	*65.97*	*66.86*	*+ 1.3%*	*.97*
PPS 10	*898*	*69.07*	*69.20*	*+ 0.2%*	*.97*
PPS 11	*704*	*73.20*	*72.55*	*– 0.9%*	*.97*
Total	*5274*	*67.90*	*67.54*	*– 0.9%*	*.97*

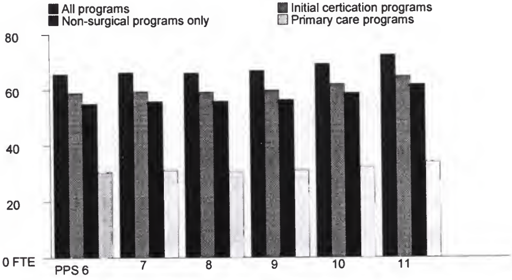
Table 8.5(b): Comparison of *YEAR-YEAR CHANGE* In Resident FTEs Claimed for Medicare Payments on HCRIS and IRIS Files — Hospital Averages, by Year

Year	*N*	*From HCRIS files (mean)*	*From IRIS Files (mean)*	*% difference*	*Correlation Coefficient*
PPS 6	*813*				
PPS 7	*980*	*+2.14*	*+2.55*	*+ 19.2%*	*.26*
PPS 8	*990*	*+4.17*	*–0.32*	*–107.7%*	*.05*
PPS 9	*889*	*–0.48*	*+2.67*	*+656.3%*	*.30*
PPS 10	*898*	*+3.59*	*+3.49*	*– 3.8%*	*.50*
PPS 11	*704*	*+1.34*	*+0.03*	*–97.8%*	*.19*
Total	*5274*	*+2.03*	*+1.70*	*– 16.3%*	*.24*

8.1.4.2 *Trends by Specialty*

Growth in residency sponsorship was analyzed by the following groups, which are not mutually exclusive: all specialties leading to initial-level board certification (that is, excluding all subspecialties); all non-surgical specialties; primary care (defined as general medicine, pediatrics, family practice and obstetrics); and hospital-based specialties (defined as anesthesiology, radiology, pathology and emergency medicine). Summary FTE statistics were also computed for first-year trainees only.

Figure 8.8: Average Program Size (Total FTEs Claimed, per Hospital) by Type of Resident, by PPS Year



Source: Interns & Residents Information System

For the IRIS sub-sample, the average number of residents claimed per teaching site grew from 66 to 73 over the six years. The total increase was 10.6%, or 2.1% per year. Figure 8.8 reveals no noticeable differences in trends by specialty type.

Table 8.6 presents the average annual change in FTEs for each of the resident subgroups, for the sample as a whole and by the academic status of the hospital that claimed the resident for GME payment purposes. Expressing these changes

Table 8.6: Average Annual Change in Resident FTEs Reported in IRIS Files, PPS Year 6 through PPS Year 11

(note: rows do not sum to total)	*All Reporting Hospitals(N=5,274)*	*By Status: Minor Teaching (N=3,890)*	*Major Teaching, not AHC (N=811)*	*Academic Health Centers (N=573)*
All residency groups	*+ 1.66*	*+ 0.65*	*+ 2.65*	*+ 7.13*
Primary Care Only	*+ 0.74*	*+ 0.43*	*+ 1.17*	*+ 2.19*
Non-Surgical Specialties Only	*+ 1.55*	*+ 0.62*	*+ 2.92*	*+ 5.86*
All Initial-Level Certifications	*+ 1.32*	*+ 0.59*	*+ 2.12*	*+ 5.18*
Hospital-based Specialties	*+ 0.44*	*+ 0.07*	*+ 0.89*	*+ 2.29*
1st-Year Trainees Only	*+ 0.22*	*+ 0.20*	*– 0.04*	*+ 0.70*

Source: Interns & Residents Information System

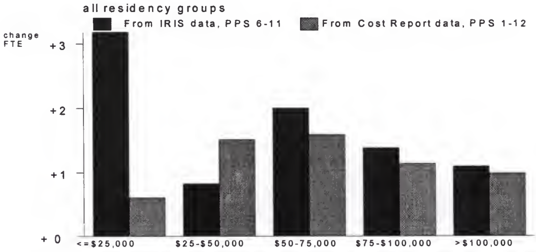
proportionally, 45 out of every 100 additional trainees were in primary care fields [1], 93 were in non-surgical fields and 80 were in initial certification programs. (The 20 that were in subspecialty programs would represent extended training time, but not net additions to the workforce.) Within academic health centers, 31 out of 100 were in primary care, 82 were in non-surgical fields and 73 were in initial level certification programs. Note that, among major non-academic teaching sites, "110 out of 100" new

[1] Example: computed as 0.74 ÷1.66=0.445

trainees would be in non-surgical specialties, which indicates that the average surgical program size actually declined within this group of hospitals.

Figure 8.9 graphs increases in total program size by groups of hospitals that have been established according to the average real GME payments received by these hospitals over the study appropriate study periods. (The second bar in this chart matches the first frame of Figure 8.7.) In the IRIS data the relationship between program expansion and per-resident payment levels is similar to that found in the cost report data over the full twelve years, except within the group of hospitals falling into the lowest payment category (under $25,000). This category is much smaller in the IRIS than in the HCRIS sample (7.6% compared to 17.4%) and is heavily influenced by a few outlier hospitals. Figure 8.9 suggests that the correlation between payment and program growth could actually be negative, depending on the influence of the hospitals in the <$25,000 category.

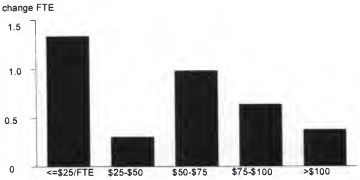
Figure 8.9: Comparison of Reported Annual Increase in Resident FTEs, by Real Total GME Payments per Resident



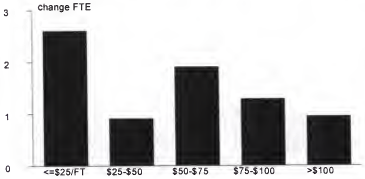
(Source: Interns and Residents Information System and HCRIS files)

Figure 8.10: Average Annual Increase in Resident FTEs, by Specialty Group, by Real Total GME Payments per Residents
(Payment categories in '000s of 1992 dollars. Source: Interns and Residents Information System & HCRIS files)

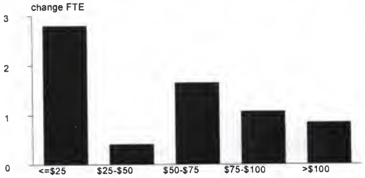
Primary Care Only:



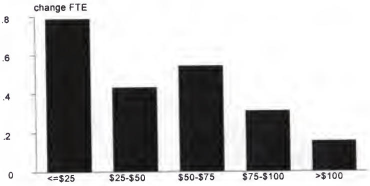
Non-Surgical Specialties:



Initial Level Certifications:



Hospital-Based Specialties:



The dissertation research questions ask if the association between payments and program growth is similar across specialty groups. Figure 8.10 therefore presents the same average annual change data from the IRIS sample, for each of the subgroups defined above. The pattern of association appears to be unchanged across residency types.

8.1.4.3 International Medical Graduates

IRIS data have also been summarized at the hospital level to determine the number of sponsored residents who are international medical graduates (IMGs). The mean proportion of IMG residents across the IRIS sample (that is, the unweighted average across hospitals) was 17.3%, but the median was 7.0%. Twenty-five percent of the sample reported sponsoring no international graduates, while 5% reported having IMGs comprise greater than 75% of their trainees.

Table 8.7: Hospital Dependence on International Medical Graduates PPS Years 6 — 11

	All Reporting Hospitals (N=5,140)	*By Status: Minor Teaching (N=3,768)*	*Major Teaching, Not AHC (N=807)*	*Academic Health Centers (N=565)*
Reported Percent IMG (unweighted mean)	*17.3%*	*16.1%*	*26.4%*	*12.4%*
Dependence Level:				
None = 0%	*31.8%*	*42.4%*	*3.7%*	*1.4%*
Low" = <=10%	*25.2%*	*21.5%*	*24.9%*	*50.4%*
Medium=10%-25%	*17.7%*	*12.6%*	*27.9%*	*37.5%*
High = >25%	*25.3%*	*23.6%*	*43.5%*	*10.6%*

Source: Interns & Residents Information System (Data missing for 134 observations

The average increase in resident FTEs among hospitals with no IMG dependence was 0.38 as compared to 2.1 for those with high dependence. Any relationship between

the two is confounded, however, by the fact that a large majority of hospitals with no IMG residents are minor teaching facilities, with small programs to begin with.

8.2 The Conversion Model Samples

8.2.1 Characteristics of New Teaching Hospitals

From a base of between 4,000 and 4,500 non-teaching short-term hospitals filing cost reports each year, between 35 and 40 meet the study definition of "converted" to teaching status. The level of teaching commitment at these sites is low — the average number of FTEs sponsored was just under three in the first year of GME participation and only five by the third year. The largest newly converted teaching site had 42 resident FTEs. New sites are predominantly affiliates of previously existing accredited programs, but there are also converted sites with newly accredited Family Medicine training programs.

Of 4,389 non-teaching facilities originally identified in the study sample in the first year of PPS implementation, 3,502 remained in operation under the same provider number and filed cost reports with usable data for all twelve years of the study period. Within this group, 7.3% converted to teaching status at some point during the 12-year period. Hospitals in large urban areas were nearly twice as likely to convert as those in smaller urban areas and over five times as likely to convert as those in rural areas. Conversion rates were similar across hospitals with varying levels of indigent care obligations, as represented by the disproportionate share index.

Converted hospitals tended to be larger (average bed capacity of 198 compared to 110 for those not converting), and had somewhat higher Medicare utilization percents

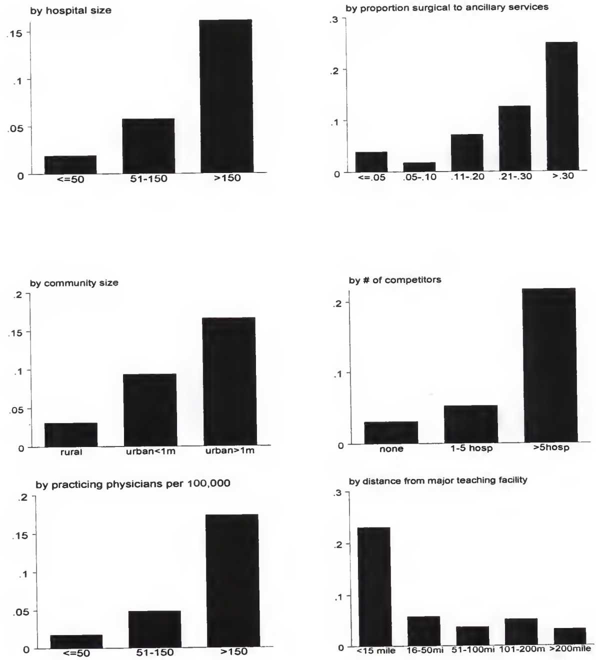
(48% compared to 45%). Average total operating margins at PPS year 1 were lower for converting than for non-converting facilities (6.0% compared to 7.8%). Hospital operating margins changed dramatically, however, during this 12-year period. In the alternative three-period conversion sample, where the baseline characteristics are measured no more than three years prior to the conversion year, total operating margins averaged 2.7% for converting as compared to 2.8% for non-converting facilities.

Table 8.8: Characteristics of Hospitals from 12-Year Conversion Sample

	Sample Total	Facilities Converting	Facilities Not Converting
Number of Facilities	3502 (100%)	255 (7.3%)	3247 (92.7%)
Mean # of Beds (at Yr 1)		198	109
Ownership (at Yr 1):			
Private, non-profit	50.1%	58.8%	49.4%
Proprietary	15.6%	22.0%	15.1%
Public	34.3%	19.2%	35.5%
Percent Urban	43.1%	75.7%	40.6%

Public hospitals were less likely to convert than private non-profit or proprietary hospitals (4% as compared to 9% and 10%, respectively). Non-teaching public hospitals are predominantly rural, however, while proprietary hospitals tend to be located in larger cities with higher levels of competition. Differences in conversion rates by ownership class are not consistent when examined within rural, small urban and large urban

Figure 8.11 Proportion of Non-Teaching Hospitals Converting to Teaching Status Within the First Twelve Years of PPS, by Service & Market-Related Covariates



categories. Moderate regional patterns can be detected in the distribution of conversions across the country. Hospitals in the Mid-Atlantic and the Pacific regions had the highest conversion rates (15.7% and 12.3%, respectively) while conversion rates in all other regions ranged from 5%-7%.

Figure 8.11 presents further differences in conversion probabilities for the 12-year sample, by categories of the main expected service delivery and market-related covariates. Each of these factors is clearly associated with the likelihood of adopting residency sponsorship, but hospital size, service levels, competition and local physician supply are also factors that are highly associated with community size. To the extent that these covariates are capturing the same, or at least highly related, phenomena, they may not all be significant predictors in a multivariate model.

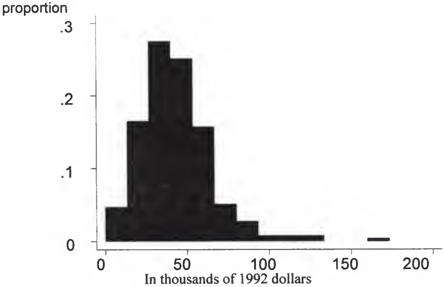
8.2.2 Potential Indirect Medical Education Reimbursement

The potential IME payment variable calculated for this model is based on the addition of three full time equivalent residents and derived from the hospital utilization and operating characteristics as of the first year of the observation period. Values range from $1,000 to $165,000 per resident. The distribution is presented below as Figure 8.12. The same variable, based on characteristics as of the middle of the twelve-year period (PPS year 6), ranges only up to $132,000 and generates a slightly more normal distribution.

Hospitals with potential IME payments of over $60,000 per resident (comprising 15% of the sample) were four times as likely to convert as those with potential IME of less than $30,000 per resident (comprising 30% of the sample). This association is likely to be confounded, however, by the fact that per-resident potential IME payments are

higher in facilities with greater absolute numbers of Medicare discharges, and/or higher case mix intensity, both of which characteristics tend to occur in larger communities.

Figure 8.12: Distribution of Modeled Indirect Medical Education Payments Per Resident, as Computed from Base Year Characteristics on the Twelve-Year Sample



In the sample as a whole, there is a strong positive association between potential reimbursement gain per resident and probability of conversion. The first frames of Figures 8.13 and 8.14 demonstrate this. If hospitals are stratified by location-related characteristics, however, the association between IME payments and teaching conversion can be substantially altered. Both location and market-related variables appear to modify the relationship between potential IME payments and the probability of conversion. Similar though less pronounced effects are seen in strata by ownership (not pictured). Bivariate findings of this sort indicate strongly that interaction terms should be tested in the multivariate models.

Figure 8.13: Proportion of Non-Teaching Hospitals Converting to Teaching Within First Twelve Years, by Potential Medicare IME Payments / Resident , by Location
(in '000s of 1992 dollars)

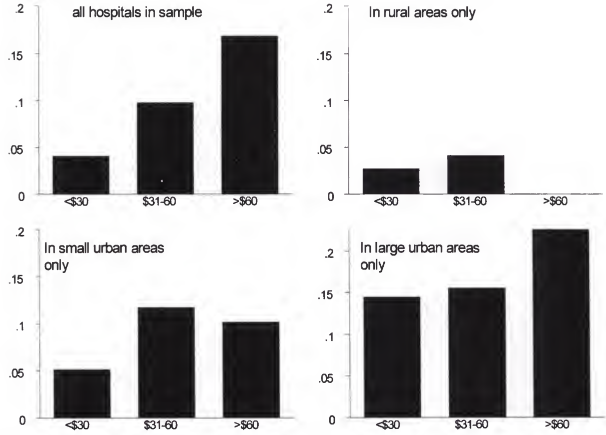
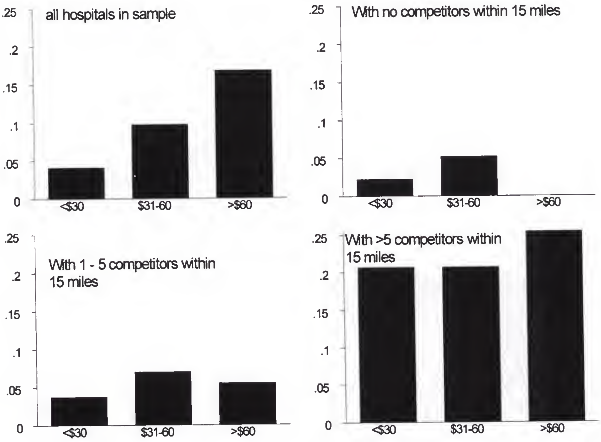


Figure 8.14: Proportion of Non-Teaching Hospitals Converting to Teaching Within First Twelve Years, by Potential Medicare IME Payments per Resident, by Level of Competition
(in '000s of 1992 dollars)



8.2.3 Trends Over Time — Contributions of the Three-Period Model

The probabilities of conversion to teaching in the alternative model specification, which looks at three sequential samples of non-teaching hospitals, are summarized in Table 8.9. The associations depicted in Figures 8.10 and 8.12 are similar to those found in the samples from the shorter observation periods, although the overall probability of

converting is lower because the observation periods are shorter for any single hospital unit.

Table 8.9: Conversions to Teaching Status in the Three-Period Model

	Group "1" Base= PPS 1 Observed PPS 2-5	Group "5" Base= PPS 5 Observed PPS 6-9	Group "9" Base= PPS 9 Observed PPS 10-12(*)
Number of Facilities	4202	4271	3914
Proportion Converting	1.4%	1.3%	2.6%
Proportion Converting, by Ownership Class:			
Private Non-Profit	1.7%	1.8%	2.9%
Proprietary	2.5%	1.5%	3.1%
Public	0.4%	0.4%	1.7%
Proportion Converting, by Potential IME Payments:			
≤$30,000 / FTE	0.7%	1.0%	1.1%
$31-$60,000 / FTE	2.0%	1.8%	3.5%
≥$60,000 / FTE	4.1%	1.3%	4.6%

(*) Constitute three-year probabilities only

By design, the sample observed over the 12-year period excludes any facilities that had a change of ownership or other merger or acquisition activity that resulted in a change in the Medicare provider number. The samples for the three-period model are able to include many of these facilities, as well as any new facilities opening after 1984. The pattern of the effect of ownership status on the probability of conversion, however, is similar across both samples. Table 8.9 describes the multiple-observation period samples and presents conversion probabilities for subgroups within period. Conversion rates were highest after PPS 9 and, for most subgroups, lowest in the middle period identified as of

PPS 5. Association between the probability of conversion and the major model covariates were similar across the two samples. It should be noted, however, that the hospitals in the last period could only be observed for three years (through PPS year 12). The proportions converting in this group reflect three-year probabilities, while those from Groups 1 and 5 reflect four-year probabilities.

9 Multivariate Study Results

9.1 Expansion Models

9.1.1 Estimation Results

This section presents results for the model in which the outcome variable is the year-to-year change in total resident FTEs claimed for IME payment. Reimbursement effect measures are computed separately for the period covering PPS Year 2 alone, for PPS 3–5 and for PPS 6–12.

All reimbursement effect measures for PPS 2 are large, positive and significant. The effects for this year are substantially higher than those found in any subsequent period. Because the initial years represent a period of hospital adjustment to the new reporting requirements under PPS, this chapter concentrates on results from the PPS 3–5 and PPS 6–12 periods. The later periods should provide a better estimation of factors affecting medium and long-range hospital decision-making, having controlled for the anomaly of the initial year responses.

Table 9.1 lays out mean, minimum and maximum values for each of the variables in the analysis. Because of the lagged variables, first-year observations are excluded from the analysis sample, and therefore also from the summary statistics. Table 9.2(a) presents findings with respect to the coefficient on the marginal IME payment variable, for the main and the final interacted effects. Interaction terms on the payment variable with ownership status and with the indicator on New York State were not individually significant, and also tested jointly non-significant. They were subsequently eliminated from the model. Complete regression output is provided in Appendix 3.2.

Table 9.1: Expansion Model Summary Statistics
(Excludes values from first observation within hospital units, due to lagged variables)

Variable	*Number of observations*	Mean	Range: Minimum	Maximum
1. Change in Resident FTEs:				
Minor Teaching	*7675*	+0.26	–135	+108
Major Teaching, not academic	*1695*	+2.31	–137	+157
Academic Medical Centers	*1181*	+6.53	–276	+269
All	*10551*	+1.29	–276	+269
Average Annual Change :				
From PPS 2 to PPS 5		+0.37	–57	+55
From PPS 6 to PPS 12		+1.87	–40	+44
2a. Real Marginal IME Payments/FTE (in '000s, lagged 1 year)	*10551*	$41.61	$0.29	$220.97
3. Annual Change in Routine Beds (units of 10)	*10551*	–0.7	–54	+43
4. Annual Change in Critical Beds (units of 10)	*10551*	+0.1	–10	+13
5. # Routine Beds in First Year of Data	*10551*	333	23	1528
log normalized(including constant):		6.01	4.89	7.40
6. Disproportionate Share Index	*10551*	0.240	0.0014	1.5023
log normalized (including constant):		–1.4741	–3.31104	0.43007
7. Ownership Categories:	*10551*			
Public		0.133	0	1
Nonprofit		0.804	0	1
Proprietary		0.063	0	1
8. Bio-medical Research Categories:	*10551*			
None		0.870	0	1
Low		0.066	0	1
Medium		0.051	0	1
High		0.014	0	1
9. Academic Status Groups:	*10551*			
Minor Teaching (not COTH member)		0.727	0	1
Major Teaching, not academic		0.161	0	1
Academic Health Centers		0.112	0	1
10. Location:	*10551*			
Rural		0.047	0	1
Small Urban (pop < 1 million)		0.387	0	1
Large Urban (pop >= 1 million)		0.566	0	1
11. Competition: # hospitals in 15 miles	*10551*			
Low (0–2)		0.156	0	1
Medium (3–10)		0.346	0	1
High (>10)		0.498	0	1
12. Total Operating Margin	*10551*	0.039	–0.99	0.99
13. Located in State w/ Medicaid GME Funding	*10551*	.774	0	1
14. Location in New York State	*10551*	0.074	0	1
15. Post Phase-In (from PPS 6 through PPS 12)	*10551*	0.665	0	1
16. Lagged Outcome: Prior-Year Total FTEs	*10551*	65.93	.001	856.41
log normalized (including constant):		3.2367	–0.4135	6.735

Table 9.2(a): Expansion Model Results Using GEE on 12-Year Panel: Results on the Marginal IME Payment Variable

N= 10,551 observations n=1,229 unique facilities

	PPS 6–12			PPS 3–5			PPS 2 only		
Outcome: Year-to-Year Δ FTEs	β	s.e.	p-value	β	s.e.	p-value	β	s.e.	p-value
All Teaching Hospitals	.019	.0076	.013	–.001	.0145	.956	.290	.0963	.003
With Interaction by <u>Teaching Status:</u> –Minor Teaching	.005	.0069	.497	–.020	.0151	.187	.258	.0914	.005
–Major Teaching Not Academic	.034	.0200	.088	.009	.0240	.393	.287	.0937	.002
–Academic Centers	.175	.0372	<.0001	.150	.0371	<.0001	.428	.1087	<.0001

Using GEE and assuming fixed intra-hospital error correlation, estimation results yield positive associations between marginal Medicare IME payments and the expansion of existing teaching programs during subsequent periods, for some subgroups of hospitals. When all teaching hospitals are examined as a single group, IME payments have a statistically significant but very small, positive effect on program expansion during the PPS 6–12 period. When the effects are dis-aggregated by teaching status, there is no significant association within minor teaching facilities during PPS 3–5 or PPS 6–12. There is a small, positive but only marginally significant (at α=.10) association among major non-academic teaching facilities during PPS 6–12. Among academic centers, however, there is a moderate, highly significant association between IME payments and program expansion during both periods.

Table 9.2(b): Expansion Model Results Using GEE on 12-Year Panel Selected Covariates

N= 10,551 observations	n=1,229 unique facilities		
Outcome: Annual Change in FTEs Claimed for Medicare IME Adjustments	Coefficient	s.e.	p- value
Patient Service-related Covariates:			
Annual change in routine beds (per 10 beds)	0.63	0.108	<.0001
Annual change in critical care beds (per 10 beds)	1.38	0.318	<.0001
Baseline size: ln(# beds as of first year of data)	1.12	0.404	.006
Mission-related covariates:			
Ln(Disproportionate Share Index)	0.66	0.191	.001
Public-ownership (reference is private, non-profit or proprietary)	0.02	0.422	.954
Bio-medical research funding category(constant $)			
None (reference)			
Low (< $18m)	0.82	0.93	.377
Medium ($18m – $70m)	3.0	1.47	.042
High (>$70 m)	4.3	2.66	.108
Academic Status (*)			
Minor Teaching facility, non-COTH member (reference)			
Major Teaching, not academic	–0.62	0.961	.519
Academic Health Center	–3.36	1.619	.038
Location & Market-related Covariates:			
Large urban status (pop>1 m, reference is small or urban)	0.28	0.249	.268
Level of Competition: # of hospitals within 15 miles			
Low (0–2 competitors, reference)			
Medium (3–10 competitors)	0.41	0.216	.058
High (>10 competitors)	0.34	0.294	.250
Other Covariates:			
Location in state with explicit Medicaid GME Funding	0.24	0.232	.295
Location in New York State	1.87	0.664	.005
Time Trends (reference is PPS Year 2):			
PPS Phase-In , years 3 – 5 (*)	4.4	2.03	.029
Post Phase-In, years 6–12 (*)	4.7	1.87	.012

(*) Results are computed from linear combinations with related interaction terms

Wald $\chi^2_{(df=24)} = 358.82$, $p<.0001$
Scale parameter: 248.57

Table 9.2(b) presents findings for selected covariates, from the specification which includes the interaction terms by academic status and time period. The variables representing changes in patient services are the model's strongest predictors. Mission-related variables are also significant. Those representing location and market characteristics were less important to the model, with the exception of the identifier for New York State hospitals.

Because the outcome is specified as a change variable, interpretation of the coefficients is not readily intuited. For those variables that are not log-transformed, the coefficient is a measure of the impact of a unit change in that variable on the level (not the rate) of annual change in the number of residents. For example, between PPS 6 and PPS 12 every $1,000 difference in the IME payment per resident in non-academic major teaching hospitals is associated with a difference of 0.034 FTEs in the expected annual change in FTEs. In the academic centers, a $1,000 change is associated with a difference of 0.175 FTEs in the expected annual change in FTEs claimed. Across all teaching hospitals, an increase of ten critical care beds is associated with an additional increase of 1.38 resident FTEs.

A more intuitive sense of the results is obtained by re-stating them proportionally, using mean values of the outcome variable for each of the hospital groups and assuming a policy-relevant level of change in the payment variable. This is presented below for the PPS 6–12 period only, in Table 9.3. Using results from the full sample of teaching facilities, a 20% increase in the marginal IME payment is associated with a nearly 10% increase in the expected year-to-year change in resident FTEs. For comparison, a 20%

percent increase in critical care capacity (an average of 7.8 new beds per facility during this period) is associated with an 56% increase in the expected year-to-year FTE change.

Table 9.3: Application of Predicted Results from Expansion Model by Teaching Hospital Subgroup

Calculated for PPS 6–12 only:	Minor Teaching	Major Teaching	Academic Health Centers	All Teaching Hospitals
Average year-to-year change in FTE	0.51 FTE	3.48 FTE	8.42 FTE	1.86 FTE
Value of a 20% change in marginal $IME received per resident	$9,800	$10,640	$7,580	$9,700
Effect of 20% increase in $IME on year-to-year change in FTE [(change in $IME/1000) * coefficient]	+0.05 FTE	+0.36 FTE	+1.33 FTE	+0.18 FTE
% Impact of +20% change in $IME on expected year-to-year change in FTE	+ 9.6%	+ 10.4%	+ 15.8%	+ 9.9%

Multivariate results for some hospital characteristics show differences with earlier descriptive findings. After controlling for other covariates, for example, the extent of indigent care obligations as measured by the DSH index is a strong predictor of residency program expansion. The same measure did not appear to be strongly associated in bivariate comparisons by discrete categories. Model coefficients on major teaching and academic health center status are significant but negative, indicating that after controlling for other covariates, increases in resident FTEs were smaller in these groups than in the minor teaching hospitals. This finding is in contradiction to the strong evidence from the descriptive study, but is attributable to collinearity with the NIH-funded research variables. At the breakpoints at which they are categorized, the research funding

measures capture characteristics that are strongly overlapping with academic status. Coefficients on the indicator variables denoting "medium" and "high" research commitment are positive and relatively large, though significant only for the "medium" level. Overlapping characteristics captured by the research and academic missions create some instability in these two variables, making them sensitive to minor changes in the model specification and/or sample definitions. NIH funding variables as a group, however, are jointly highly significant ($\chi^2_{df=1} = 6.89$, p=.009), and alternative specifications using a transformed continuous variable also result in a highly significant positive coefficient.

Location and competition variables have similar problems of multi-collinearity. In bivariate and stratified bivariate analyses both urban size and numbers of competitors appeared to be associated with increased GME sponsorship. In the multivariate model they are no longer individually significant, although a test for joint significance of all three location variables is positive ($\chi^2_{df=1} = 7.44$, p=.006). Year-to-year increases in hospitals located in New York State averaged 2.0 FTEs greater than those for hospitals in other states. In the multivariate model there was no significant effect from being located in states with explicit Medicaid funding for GME, after controlling for the "New York effect".

The coefficient on the variable for lagged total operating margins (not shown) was positive but not significant. Operating margins showed pronounced secular changes during this period, dropping precipitously in the first five years, then gradually recovering by PPS 12. It is possible that any relationship between operating margins and residency

program expansion has been masked by secular trends that are not adequately captured by the time trend variables included in this model.

Due to the change-value specification of the dependent variable and the presence of extreme positive and negative outliers, the model variance is high. Trimming the sample to exclude observations with y-values beyond three standard deviations from the mean reduces the variance considerably (the scale parameter, analogous to a mean squared error term in an ordinary linear regression, drops from 248.6 to 78.5). Trimming the sample disproportionately excludes the large academic programs from the analysis, however, which introduces an unacceptable sampling bias. Regressing average annual FTE change values from PPS 6 through 12, against averaged capacity changes and other covariates measured at the beginning of that period provides a better alternative approach that can be used to reduce the effects of the year-to-year noise with less systematic effects on the sample. As shown in Table 9.4, OLS regression on the average annual change for the PPS 6–12 period produces coefficients on the payment variable that are very similar to those produced for the same period through the GEE analysis.

Table 9.4: Comparison of Results from Average Annual and Year-to-Year Change Models, PPS 6–12 Period Only

	β	s.e.	p- value
Outcome: Average Annual Change in FTEs over 6-year period (OLS w/ clustering)			
Minor Teaching	–.005	.011	.655
Major Teaching, Not Academic	.04	.015	.007
Academic Centers	.16	.028	<.0001
Outcome: Year-to-Year Change in FTEs (GEE w/ interaction term for IME payment by PPS 6–12)			
Minor Teaching	.005	.0069	.497
Major Teaching, Not Academic	.03	.020	.088
Academic Centers	.18	.037	<.0001

With the exception of the variable for lagged total operating margin, the two models produce coefficients on the covariates that are also similar in direction and magnitude. The coefficients on public ownership and biomedical research levels have narrower standard errors in the OLS model, such that mission-related characteristics as a group appear as more significant predictors of expansion. A similar regression with observations from Year 2 on the average change over the PPS 2–5 period produces non-significant coefficients on all three types of teaching institutions.

9.1.2 Model Fit & Diagnostics

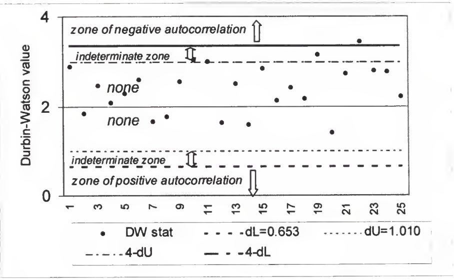
Beyond the Wald chi-square statistic assessing the joint contribution of all X's (reported at the bottom of Table 9.3(b)), there are no diagnostic tests developed at this time to assess goodness-of-fit in GEE applications with continuous outcome variables. One approach to assessing the adequacy of the estimating equation is to examine explained variance in the OLS model, before accounting for error correlation. Because of the inherent noisiness of the change variable, the R^2 on an OLS version of this model is only .06. If the outcome variable were specified as the absolute number of FTEs, the same set of independent variables using the same estimation technique would explain 79% of the variation in total FTE numbers over the PPS 2 –12 period. The figure drops only to 74% if the lagged dependent variable is excluded from the equation. In a random effects version, the over-all R^2 is also .74, and in a fixed effects version it is .45. Although explained variance cannot be compared across different outcome variables, results from models predicting absolute numbers of FTEs do provide some evidence that the independent variables are appropriate measures to operationalize the hospital demand model from Chapter 5.

The regression of average annual change in FTEs on the set of independent variables from PPS 6 had a F-statistic of 23.9 (degrees of freedom, 20 and 808) and an R^2 of .37. Using OLS to estimate average annual change is less efficient than GEE in the sense that fails to make use of most of the years of information from the covariates. However, the simpler estimation technique has some advantages. It provides an opportunity to assess the validity of the mean function (choice and specification of the independent variables) without the noise of the change specification. A case could be made that factors affecting medium or even long-term trends in the growth of residency sponsorship are more relevant to the research question than factors affecting any individual year. In that case, growth rates derived from longer periods may be the more appropriate outcome of interest.

As mentioned in Chapter 7, GEE produces consistent estimates of the regression parameters and their variances even when the constraining assumptions regarding the structure of the within-cluster error correlation are incorrect, provided the original equation is properly specified. The fixed within-hospital correlation obtained from the GEE estimation of the Expansion model is –0.069, small enough to consider that an assumption of independence might also produce reasonable estimates. In general, variables expressed as change-values often show patterns of negative auto-correlation. Imposition of an auto-correlated structure on the Expansion Model, however, was ruled out on three grounds. First, visual inspection of a plot of OLS/Huber-White model residuals against the eleven years in the analysis sample revealed no patterns indicative of auto-correlation. Second, a formal test for auto-correlation was conducted using a random sample of 25 hospital units, drawn from those hospitals in the study sample that

contributed data in all years. Durbin-Watson (DW) statistics were computed on regressions of the year-to-year change in FTEs against the policy variable of interest, individually for each hospital unit. As diagrammed in Figure 9.1, DW statistics fell within the "no auto-correlation" range in 21 out of the 25 estimates, within the indeterminate negative zone in three, and in the clear negative zone in only one series. These test results provided no evidence of serial auto-correlation in this data, and justified the use of a lagged marginal IME payments to control for endogeneity among right-hand side variables.

Figure 9.1: Distribution of Results from Durbin-Watson Tests for Serial Auto-Correlation on Random Sample of 25 Teaching Hospital Units



Finally, GEE options allow for estimation without imposing any constraints on the error term — that is, under the assumption that errors within hospital units are correlated but without the imposition of any known pattern to the correlation. When a GEE estimate is conducted without such constraints, the regression produces estimates of the within-hospital pair-wise correlation that can be visually examined to identify possible patterns, which can then guide the GEE modeling decision.

GEE with unstructured correlation would not converge when run on the Expansion Model sample, until the variance of Y was reduced by eliminating observations with FTE changes in excess of three standard deviations of the mean. One hundred eighty-eight observations, or 1.8% of the sample, had to be dropped. The correlation matrix produced by GEE on the reduced sample, however, also produced pair-wise correlations that showed no auto-regressive or other recognizable patterns. Their values ranged from –0.25 to + 0.15. Both the fixed and the unstructured correlation options produced similar parameter estimates. The parameter estimates from GEE assuming independence (i.e. no correlation) were higher for all categories of the payment variable.

9.1.3 Secondary Analyses from IRIS Sample

Sub-analyses by type of program specialty and other resident characteristics are conducted using the same models as discussed above, but using dependent variables constructed from the IRIS data. Regression results for selected covariates are summarized in Table 9.4. (Complete regression output for each of the models, and related diagnostics are included in Appendix 3.3.) The sub-samples for first-year trainees and for the IMG trainees are smaller than the others due to additional exclusions made necessary by missing FTE data.

All of the secondary analyses yield non-significant results for the payment policy variable of interest. The association between marginal IME payment per resident and program growth is not statistically different from zero whether the change in sponsorship is measured for all residents, for first-year residents only, for non-surgical specialties, for residents in initial certification programs, for primary care specialties, or for residents in

hospital-based specialties. The interaction terms on IME payments by type of teaching facility were non-significant even at an α =.10 level in all secondary analyses. For comparability with Table 9.2, the effects of the payment policy variable are still presented separately by type of teaching hospital.

Table 9.5: Results from Secondary Analyses on IRIS Data, Using GEE on 6-Year Panels

Outcome:	Average change: All FTEs	1st year trainees	Initial certification	Non-surgical trainees	Primary care	Hospital-based	IMG
# observations	3771	3605	3771	3771	3771	3771	3761
# unique hospitals	1062	992	1062	1062	1062	1062	1059
Δ FTE: mean	1.81	0.24	1.47	1.68	0.81	0.48	1.36
Standard deviation	18.43	1.47	16.96	16.10	10.10	4.81	7.98
Wald χ^2	100.8	19.05	84.76	118.18	49.79	105.8	11.48
p-value	<.0001	.5189	<.0001	<.0001	.0002	<.0001	<.0001
Real Marginal IME payments for last resident sponsored (in $'000s)							
Among Minor Teaching Hospitals	–0.01	–0.01	–0.01	–.01	–.003	-0.0001	0.002
Among Major Teaching Hospitals	0.02	0.01	0.01	–.0004	–003	–0.01	-0.036
Among Academic Health Centers	–0.03	0.02	–0.06	–.005	0.04	–0.01	-0.046
<u>Patient Service-Related Covariates</u>							
Change in routine beds (per 10)	0.50 *	–0.11	0.46 **	0.40 ***	0.24	0.07 *	–0.05
Change in critical care beds(per 10)	0.66	0.80	0.47	0.71	0.10	0.12	0.02 *
<u>Mission-Related Covariates:</u>							
Ln(Disproportionate Share Index)	0.64	0.38	0.96 **	0.92 **	0.53 *	0.15	0.70
Public Ownership	0.14	0.19	0.06	0.15	–0.37	0.34	0.01
Bio-Medical Research (ref: None):							
Low (<$18 m)	2.2	–0.46	2.0	1.8	0.95	0.40	3.0 *
Medium ($18 - $70m)	2.7	–2.8	0.90	0.50	0.79	–0.72	1.9
High (>$70m)	10.8 *	–2.5	10.0 **	12.9 ***	3.0	4.0 ***	3.3
Academic Status (ref:Minor Teaching)							
Major Teaching, not academic	–1.7	–2.0	–1.3	0.08	–0.34	0.85	2.5 **
Academic Health Center	1.7	–1.2	2.7	0.80	–1.8	1.8	-1.5
<u>Other Covariates:</u>							
Location in State w/ Medicaid GME							
Location in New York State	1.7 *	–0.21	0.87	1.0	0.29	0.13	1.5
Baseline Size: ln(beds) at year 6	1.7 ***	0.67	1.1 *	1.3 **	0.40	0.46 **	0.64 *
ln(total FTEs) at prior year	0.38 *	0.14	0.40 **	0.41 **	0.23 *	0.12 **	0.47 ***

*p<= .10 ** p<=.05 *** p<=.01

The explanatory power of the models is highly variable across the different resident subgroups, but only moderate at best. The model for 1st year trainees produces no significant coefficients on any of its covariates. Even in these fairly weak models, the strongest correlates of expansion in residency sponsorship continue to be patient service-related (change in bed capacity) and mission (disproportionate share obligations and research commitment).

There are no discernable patterns in the strength of association, however, by type of resident. Most of the explained variance in each of the models is probably derived from the control variables for baseline hospital size and prior-year FTE.

The alternative specification, regressing average annual change in IRIS FTEs against the covariates as of PPS 6, also produced no significant association between payments and resident sponsorship changes. The explanatory power of these estimations was only marginally better than the year-to-year version; the highest R^2 values were for estimations of hospital-based trainees (.24) and the lowest were for the estimation on 1st-year trainees (.05). However, coefficients on the two average change in bed capacity measures tended to be larger, with smaller standard errors, than their equivalent coefficients in the GEE models.

The IRIS data permit hospitals to be grouped by levels of dependence on international medical graduates, as described in Chapter 8. Separate regressions on the change in total resident FTEs, within groups of hospitals stratified by their level of IMG dependence, also yield inconclusive results. There are insufficient numbers of observations to include interaction by teaching status within the strata. First-order effects

of the IME payment variable, however, are close to zero in magnitude and non-significant, regardless of the level of dependence.

The predominantly negative findings of all of the IRIS models are most likely to be the result of increased measurement error in the IRIS files. Because the IRIS reports are only available for PPS 6-12 and only for a subset of all teaching hospitals, it is also possible that the different coefficients obtained for ΔFTE from the IRIS source and ΔFTE from the cost report source is the result of sampling differences. In order to assess the extent of differences in IRIS results that are attributable to factors other than measurement error, two tests were conducted on the original Expansion Model equation using the dependent variable as computed from cost report data, but restricting the estimation to the sample as defined by IRIS data. To test the impact of the restricted time period on the main model, an indicator variable for PPS 6-11 only was computed and interacted with the IME payment variable, and the estimation was run on all observations in the PPS 6-12 period. Neither the main or interacted variables identifying the IRIS study period produced significant coefficients, indicating that the loss of PPS year 12 to the IRIS sample should not have biased the results.

A similar approach was used to test for selection bias attributable to the exclusion of non-reporting hospitals. The same equation is estimated, but the sample is restricted to the IRIS period and first and second order (interaction) terms are added for dichotomous variable indicating whether IRIS data were available for that observation. The coefficient on the main indicator is positive and marginally significant (2.3, $p = .093$) though the coefficient on its interaction term is not (–0.03 $p =. 204$). The non-significant interaction term indicates that, even if the IRIS reporting hospitals tend to have larger increases in

residents than the non-reporting hospitals, the influence of the IME payment on the increases is no different between the two groups. With respect to the payment policy effect within the applicable six-year period, therefore, no selection bias is evident from the exclusion of IRIS non-reporting hospitals.

9.2 Conversion Model

9.2.1 Estimation Results & Diagnostics

Table 9.6 presents summary statistics on the analytic sample for the model observing non-teaching hospitals from PPS year 1 over the first 12 years of PPS implementation. Logistic model results on the probability of converting to teaching status are presented in Table 9.7, expressed as odds ratios using exponentiated coefficients. For comparison, results from the multi-period 4-year probability model are included in the last three columns. The 12-year model provides a moderately good fit (chi-squared statistic for likelihood ratio test = 223.98, p<. 00001, pseudo-R^2 of .143). The multi-period model results are similar. Complete regression outputs for both models are provided in Appendix 3.4.

The coefficient on the variable representing potential reimbursement gain per resident is close to zero (0.0052) with a standard error of 0.0039 ($p = .19$). The measure of association on the IME payment variable is virtually unchanged whether the equation estimates 12-year or 4-year probabilities. Tests for effect modification were conducted using interaction terms of the IME payment variable by hospital size, ownership, DSH levels and location.

Table 9.6: Conversion Model Summary Statistics (12-Year Observation Sample)

	Proportion	Sample Total	Facilities Converting	Facilities Not Converting
Number of Hospitals in Analysis Sample (*)	*1.00*	3352	250	3102
1. Potential IME Payments per Resident, @ 3 FTEs (mean, $1992)		$33,299	$43.124	$32,507
2. Hospital Size				
<= 50 beds	*.29*	977	19	958
51-150 beds	*.44*	1472	84	1388
> 150 beds	*.27*	903	147	756
3. Surgery proportion to total ancillary costs				
1 (<= 5%)				
2 (5%–10%)	*.05*	182	6	176
3 (10%–20%)	*.17*	575	10	565
4 (20%–30-%)	*.56*	1888	137	1751
5 (> 30%)	*.20*	652	83	569
	.02	55	14	41
4. Indigent Care Obligation (from Medicare DSH index)				
Low (<=.15)	*.52*	1762	133	1599
Medium (.15-.30)	*.32*	1087	75	1012
High (>.30)	*.16*	533	42	491
5. Ownership				
Non-profit	*.50*	1683	147	1536
Proprietary	*.16*	538	56	482
Public	*.34*	1131	47	1084
6. Physician Supply (patent care physicians per 100,000 population, by county)				
Low (<=50)	*.19*	639	12	627
Medium (50-150)	*.56*	1872	92	1780
High (>150)	*.25*	841	146	695
7. Location & Market (competitors defined as short term acute care hospitals within 15 miles)				
Rural, no competitors	*.32*	1064	30	1034
Rural, 1+ competitors	*.23*	784	28	756
Urban, no competitors	*.06*	188	10	178
Urban, 1-5 competitors	*.21*	714	53	661
Urban, >5 competitors	*.18*	602	129	473
8. Distance from nearest major teaching facility				
< =15 miles	*.15*	497	114	383
> 15 miles	*.85*	2855	136	2719

(*) 3,502 hospitals met sample inclusion criteria with respect to cost report data. Of these, 150 providers were subsequently excluded from the analysis sample because the components to the DSH index were not available in the PSF tapes during any of the twelve years of data.

Table 9.7: Conversion Model Results (12-Year and 4-Year Observation Periods)
Logistic Regression with Robust Standard Errors

	Single Observation Period N=3,352			Three Observation Periods N=11,411 (4.167 unique providers)		
Outcome: 1 if converted to teaching during observation period; 0 if not	exp^{β} (Odds Ratio)	s.e.	p-value	exp^{β} (Odds Ratio)	s.e. (robust)	p-value
Potential IME Payments per Resident	1.0052	0.00395	.189	1.00	0.004	.989
Service Related Covariates:						
Hospital Size (ref: <50 beds)						
51-150 beds)	1.72	0.484	.052	1.47	0.397	.159
>150 beds	3.03	0.913	.000	2.09	0.599	.010
Service Level Index	1.21	0.147	.113	1.35	0.132	.002
Mission-related covariates:						
DSH Index (ref: Low)						
Medium	1.26	0.205	.158	1.03	0.179	.873
High	1.92	0.396	.002	1.65	0.324	.011
Ownership (ref: non-profit)						
Proprietary	0.82	0.147	.280	0.73	0.131	.082
Public	0.99	0.184	.939	0.80	0.187	.340
Market-related covariates:						
Physician Supply (ref: Low)						
Medium	1.49	0.480	.211	1.96	0.872	.131
High	2.51	0.860	.007	3.58	1.671	.006
Location & Market (ref: Rural, no competitors)						
Rural, 1+ competitors	1.03	0.287	.920	0.69	0.231	.263
Urban, no competitors	1.47	0.545	.302	0.89	0.428	.808
Urban, 1-5 competitors	1.33	0.352	.283	1.39	0.386	.234
Urban, >5 competitors	2.01	0.644	.029	2.02	0.668	.034
Located <=15 miles from major teaching facility	1.73	0.371	.010	1.48	0.312	.060
Time trend:						
PPS 5 Group Indicator				0.82	0.159	.309
PPS 9 Group Indicator				1.66	0.293	.004
Log Likelihood:	*-762.31*			*-921.44*		
Likelihood Ratio Test	$\chi^2_{df=15} = 223.98, p<.00001$			$\chi^2_{df=17} = 243.15, p<.00001$		
Pseudo-R^2	*.143*			*.119*		

All interaction terms were non-significant ($p >. 25$ for every term except IME payment x hospital size, for which $p =. 07$). Interaction effects of the payment variable by the time trend indicators were also tested in the 4-year probability model, and were not significant at the $\alpha = .10$ level.

As in the Expansion Model, covariates representing patient service delivery and mission are significant predictors of participation in graduate medical education. Unlike the Expansion Model, covariates related to location and market characteristics are also strong predictors, including local physician supply and proximity to a major teaching facility

Over the first twelve years of PPS, the sample probability for converting to teaching is .08. Controlling for all other covariates, hospitals with 150 or more beds are more than three times as likely to convert than those with under 50 beds (95% CI: 1.68 – 5.47). The 5-level ordinal measure of surgical costs as a proportion of total ancillary costs is not a significant independent predictor in the 12-year sample, but it is significant in the 4-year probability model (p=. 002). Hospitals with high indigent care obligations are nearly twice as likely to convert as those with low obligations (95% CI: 1.28-2.88). After controlling for other covariates, ownership categories, however, are no longer significant factors in predicting conversion.

Hospitals located in counties with the highest physician supply ratios are 2.5 times as likely to convert as those in counties with the lowest (95% CI: 1.28-4.91). Those located within 15 miles of a major teaching facility are 1.7 times as likely to convert as those located at greater distances (95% CI: 1.14-2.63). The combined location/ competition variable is not significant except at the highest level. Hospitals located in

urban areas with greater than five competitors are twice as likely to convert as those in rural areas with no competition (95% CI: 1.07 – 3.77) and 1.96 times as likely to convert as those in rural areas with any competition. A cumulative Wald test for equality of the coefficients on urban locations across three levels of competition found no significant difference in the 12-year model ($\chi^2_{df=2} = 3.14$, p=. 208).

In the model with multiple observation periods, the time trend for the PPS 5 hospitals is not significantly different from the reference period (PPS 1). Observations from the PPS 9 period were 1.7 times as likely to convert as those from the initial period (95% CI: 1.2 – 2.3), even though these hospitals were followed for three rather than four years.

A second version of the 12-year probability model was conducted using a potential IME payment variable constructed from hospital characteristics at the middle of the observation period (PPS Year 6). The purpose of the alternative specification was to investigate possible bias attributable to the application of modeled IME adjustment rates to the base DRG payments in Year 1, when these rates still represented a blend of the federal and hospital-specific historical costs. Model results were virtually identical, in both coefficients and standard errors, between these two specifications.

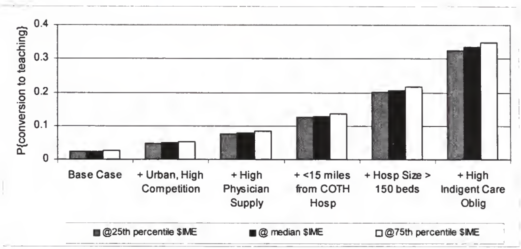
9.2.2 Predicted Conversion Probabilities

The effect measures noted in the previous section can be placed in context by computing their impact on the predicted probabilities of converting to teaching status, within likely groups of hospitals. At the beginning of the PPS implementation, the "modal" non-teaching hospital (i.e. most typical, based on sample frequency) was private non-profit, between 50 and 150 beds, located in a rural area with no competition, in a

county with between 50 and 150 practicing physicians /100,000 population, had a DSH index score of less than 0.15 and a surgery proportion of 10%-20%. The predicted 12-year probability of conversion for a hospital with these characteristics is only .025, compared with the actual sample average of .081. A hospital with the "least likely to convert " combination of covariate characteristics has a predicted probability of only .007, while the prediction for one with the "most likely to convert" characteristics is .476. Figure 9.2 illustrates the influence of the strongest determinants of teaching conversion, taking the modal hospital described earlier as the base case. Selected factors are then altered sequentially. Predicted probabilities represent their cumulative impact.

Figure 9.2: Cumulative Effect of Altering Selected Predictors on 12-Year Probability of Conversion For Most Typical Non-Teaching Hospital

(12-Year probabilities)



To illustrate the difference in proportional impact between variations in the selected main covariates and variation in the payment policy variable of interest, each of the probabilities is computed separately for a potential IME payment equal to the sample 25^{th} percentile, median and 75^{th} percentile. Because the coefficient on the payment variable is not statistically significant in the model, the three levels cannot be said to be significantly different from each other.

10 Discussion & Policy Significance

10.1 Interpretation of Results

Taken as a whole, the two Expansion Models and the Conversion Model provide only limited evidence that Medicare's GME-related payments were an important factor in GME sponsorship decisions. The conceptual model introduced in Chapter 5 described hospital demand for GME as a function of both financial factors and a set of non-financial factors that included service needs, institutional mission and competition. The principal study questions ask the following: after controlling for the non-financial factors, did Medicare GME payments influence the expansion of residency training among new or existing teaching hospitals; if they did, was the strength of influence similar across types of teaching institutions and types of residents? Interpretation of the multivariate findings requires both a review of the results with respect to the specific model hypotheses, and an assessment of the model's ability to control for non-financial factors.

The main hypothesized effects were that $\beta_{\$IME}$ would be positive though small, whether the outcome variable measured change in sponsorship among existing programs, or was a 0/1 variable denoting acquisition of any resident sponsorship for the first time. The $\beta_{\$IME}$ conditioned upon hospital academic status were expected to be significantly different across the three types of teaching institutions. The strongest effects were predicted to occur within the larger community-based programs, defined as non-academic COTH members.

Among existing teaching programs, the influence of Medicare payment policies on hospital sponsorship decisions varies by time period. The effects measured for PPS year 2 are substantially higher than those found in any subsequent period. It is reasonable to conclude, however, that this difference does not reflect a single year of altered decision-making with respect to residency sponsorship. Measures from PPS 2 are more likely to be the product of adjustments in hospital residency certification and reporting during the initial year of the regulations, coupled with the increase in marginal payment that was artificially caused by the phase-in of federal DRG rates. Across several different specifications of the Expansion Model, the consistent story appears to be as follows: after a settling-in period during the first few years of PPS implementation, Medicare payment incentives had a moderate influence on teaching sponsorship decisions within the academic centers, but did not influence decisions among the smaller programs. Among the larger community-based programs, the reimbursement effects are not clear; some models show a small, significant association, others are non-significant, but none of them produce a numerically large effect measure within this group. The study provides no evidence that potential reimbursement gains influenced the decisions of non-teaching hospitals to adopt teaching activities.

Contrary to the hypothesis in Chapter 5, the models estimate strongest effect measures within academic medical centers rather than within the large community based programs. The mean annual increase in residents in the non-academic group is much smaller that the mean among academic centers (+3.5 FTEs compared to +8.5 FTEs, respectively), so the difference in proportional effect is not as great. The model using average annual change in FTEs, for example, produced a significant effect during PPS 6–

12 among the major non-academic programs of + 0.04 FTEs per $1,000 difference in IME payment. This is one fourth the absolute size of the effect measured by the same model, among academic centers. Proportional to the expected annual change in residents in each group, the reimbursement effect among non-academic sites is only one half as strong as that measured in academic settings.

Secondary study questions asked if the association between Medicare payments and sponsorship change was different by type of resident. The secondary hypotheses were that the $\beta_{\$IME}$ estimated for changes in residency sponsorship by specific specialty groups, by first-year post-graduates and by residents who are graduates of international medical schools, would be significantly different from each other. Payment effects were expected to be stronger for non-surgical specialties than for other specialty groups, and stronger for international medical graduates than for all FTEs.

The secondary study questions required the use of IRIS data to derive FTEs by resident type. Findings based on the IRIS data are uniformly negative with respect to the payment policy variable. The IRIS reporting hospitals represent a type of convenience sample that is subject to problems of external validity. However, testing on the IRIS sample was not able to identify bias attributable to either the restricted time period or the group of non-IRIS reporting hospitals. Negative results from IRIS data are probably the result of non-systematic measurement error, which created a bias to the null across all types of residents examined. This made it impossible for the model to answer any of the study questions with respect to specialty type, or to examine the possible differences in model results when the study question was restricted to the effect on first-year trainees. This is unfortunate in the context of the positive findings among academic centers when

the model was based on cost report FTEs. It is possible that the positive association between payments and program expansion is present when estimated with total FTEs, but not present (or substantially smaller) when estimated with first year trainees. The two results would have different implications for the role of Medicare payment policy in influencing total physician production. Restricting the dependent variable to counts of first-year trainees would have provided the best way to control for possible confounding effects of lengthened training times among specialists that may have preferentially influenced the FTE growth found in academic settings.

The Expansion Models appears to confirm the conventional wisdom that much of residency sponsorship changes are driven by patient service needs. Across all specifications of the model examining change in residents within existing programs — even in the relatively weak models using IRIS-derived resident FTEs — changes in bed capacity were consistently strong predictors of changes in resident numbers. The differences in effect between the routine and the critical care capacity variables are difficult to disentangle, because in some settings new critical care beds substituted for routine beds, while in others (especially the academic sites) both kinds of capacity grew simultaneously. Growth in critical care capacity, however, can be assumed to reflect a more general trend in technology adoption.

Of all the covariates in the Expansion Model, those intended to represent changes in patient service delivery provide the most plausible competing causal factors for potential influences on sponsorship decisions. Mission-related attributes such as academic affiliation and level of research commitment serve primarily as contextual variables, identifying the settings in which program expansion is likely to occur without

serving as the mechanism or the causal link. The association between research commitment and growth in sponsorship, for example, has little to do with the use of trainees in the conduct of research (they would not be included in the IME FTE count in any event). Rather, it reflects the likelihood that research is conducted and funded in settings with extensive subspecialty faculty, and such faculty are also necessary for the accreditation of specialty training opportunities. As discussed in Chapter 3, much of the total growth in resident FTEs has occurred as a result of the extension of total training time through sub-specialization.

The DSH index value, as a measure of indigent care obligation, is identified in the conceptual model as a mission-related covariate. It may also be considered a service-related variable, to the extent that it relates to the hospitals' needs to staff outpatient clinics and provide community primary care. The consistently positive association between the logged DSH index and residency program growth across all model specifications can be interpreted as additional evidence of the strength of hospital demand for resident labor to meet service needs.

The conceptual model also discusses the role of non-price competition in training decisions. Residency training is identified as a potential basis on which to compete for physician loyalty, because GME commitments offer both status and work relief to the community hospitals' attending physicians. Numbers of nearby competitors and physician supply measures were entered into the models to control for non-price competition. The Conversion Model includes both types of competition variables, although greater physician supply ratios would be expected to occur in communities with more local hospital competitors. Both variables are significant predictors of conversion

to teaching status, supporting the idea that community hospitals use residency programs to compete for admitting staff.

10.2 Policy Relevance: Numerical Significance in the Context of The Balanced Budget Act of 1997

The magnitude of the payment policy effects in the model appears small, although the proportional effects as presented in Table 9.3 are not small within their hospital groups. The elasticities generated for major teaching and academic hospitals are roughly 0.5 in the non-academic settings (meaning that a 1% change in payment is associated with a 0.5% change in expected FTE growth), and 0.8 in academic hospitals. The comparable elasticity for a change in critical care capacity from that model is a great deal higher, at 4.4 for the full 12-year period, and nearly 3 if the calculation is restricted to the PPS 6–12 period. Critical care capacity is not a variable subject to direct policy intervention, however, while Medicare IME payment clearly is. The relevant policy question is whether the magnitude of the reimbursement effects found by these models is sufficient to make a difference in total physician training decisions, within the bounds of what might be considered politically feasible intervention in the payment variable.

The Balanced Budget Act of 1997 made several changes to the Medicare GME payment rules which can provide the regulatory context to answer this question. It includes phased-in reduction of the IME payment formula between 1998 and 2001 that will eventually reduce payments by 40% (from 7.7% to 5.5% per increment of .10 in the resident-to-bed ratio). This rate can be used to model the difference in the average annual change in FTEs for the PPS 6–12 period, had the new rate been in effect at that time.

I have simulated this change using the coefficients from the model of average annual change in resident FTEs regressed against characteristics as of PPS year 6. The

marginal IME payment is altered to what would have been paid had the full BBA reduction in IME (– 40%) been in effect in PPS 6. An outline of the computation and its results is provided as Table 10.1.

Table 10.1: Simulated Effect of 40% Reduction in Marginal IME Payments, Occurring in the PPS Year 6

	Minor Teaching	Major Teaching, not AHC	Academic Health Center	All Teaching Hospitals
Number of Hospitals (PPS 6)	719	158	106	983
Mean Total Resident FTE, at PPS 6	23.3 FTE	111.5 FTE	250.5 FTE	62.0
Average Annual Change in FTE, PPS 6-12	+0.40 FTE	+3.24 FTE	+7.99 FTE	1.67
Mean Number Years Contributed by Each Hospital, between PPS 6 and PPS 12	6.41	6.75	6.97	6.53
Mean Total Resident FTE, at PPS 12 (or latest year)	25.9	133.4	306.2	
Mean Payment Effect of 40% Reduction in IME, per Resident FTE	–\$17,141	–\$19,917	–\$14,035	–17,252
Applicable Model Coefficient (β_{IME})	–.0047	+.0411	+.1632	
Predicted Effect of Payment Change on Residency Growth, Per Year (β_{IME}* Payment Effect)	+0.08 FTE	–.82 FTE	–2.29 FTE	–0.32 FTE
Mean Predicted Effect of Payment Change on Residency Growth, Total for Period	0.53 FTE	-5.56 FTE	-15.99 FTE	–2.23 FTE
Total Predicted Effect of Payment Change on Residency Growth, All Hospitals				–2,192 FTE
Total Number of Residents Claimed for IME in PPS Year 12 Sample				77,055 FTE
Cumulative "Payment Effect" as % Actual Number Claimed in PPS 12				**–2.8%**

The modeled effect of IME payments in the growth of residency sponsorship for the PPS 6–12 period, across all types of teaching hospitals, represents less than 3%

reduction to of the number of trainees claimed for IME payment by the end of the period. This is a small impact relative to the actual growth in residents during this period.

Assessment of policy-significance, as distinct from statistical significance, is a research judgement call. In the context of other known trends such as increased hospital case acuity, critical care, other technology diffusion and the development of subspecialty fields during the PPS 6–12 period, the added incentive for sponsorship growth that was contributed by the higher Medicare IME payments does not seem substantial.

In a second regulatory change, the BBA placed a cap on the number of residents that could be counted for IME purposes. The cap is derived from moving averages over three prior years, but its eventual effect is to reduce the marginal Medicare reimbursement (i.e. the payment effect from adding residents) to zero. The relevant question becomes, given the model findings and hospital characteristics as of PPS 12, how much effect would there be from eliminating incremental IME payments altogether? Extending the model to predict future sponsorship changes is not an appropriate use of regression results. It may, however, be reasonable to draw some qualitative conclusions for this scenario based on the importance of the reimbursement variables relative to contribution of other factors in the model. The most important contribution of this study may be that it suggests strongly that GME sponsorship decisions are driven by factors other than reimbursement maximization. Even the elimination of all incremental reimbursement gain from the decision to add residents may not be enough to substantially alter hospital decisions.

In Chapters 2 and 3 of this dissertation I tried to place the research study questions in the context of national health workforce policy objectives as well as

Medicare financial and budget goals. From the data in Chapter 3 it is clear that modifications of the Medicare GME payment rules are important for financial policy reasons, to secure budget objectives and to promote payment equity across hospitals. The objective of this dissertation, however, has been to determine if GME payment changes are also effective as a lever to encourage reductions in physician training as part of a federal workforce policy to reduce future physician surplus. The empirical work found evidence of some influence of GME payments on residency sponsorship settings, but the influence is not strong. Reimbursement regulation would not appear to be an effective federal workforce policy tool.

10.3 Study Limitations

This is a retrospective observational study using available secondary data sources to examine influences on hospitals' medical education decisions. The study's chief limitation is that it looks back on a period of overall expansion in teaching activities, in order to answer policy questions about hospital decisions in a future of stable or contracted teaching activities.

The dissertation does not attempt to develop an economic model of hospital demand for resident labor. In the context of a secondary data study, the strongest factors affecting graduate medical education decisions are probably unobservable. Developing a comprehensive demand model would require management engineering data for specification of a hospital production function. Perhaps even more important, it would need to address the complex issues of measuring hospital motivation from educational objectives, non-price competition and other components to an institutional objective function. This is a task that can only be achieved with the help of extensive surveying of

hospital executives and training program directors. The dissertation's quantitative models represent a more limited approach of risk assessment, as they attempt to quantify the independent contribution of reimbursement incentives after controlling for effects of expected covariates that include very rough proxies for resident labor substitution and non-price motivations.

Within the more limited objectives of the secondary data study, there are other limitations worth noting. Even though several sources were obtained to measure the growth of hospital-based GME sponsorship, hospital reporting of resident FTEs is subject to measurement error that can be reduced but not eliminated by consulting alternative data sources. The change specification of the dependent variable contains extreme outlier values which influence model results, but which are difficult to control for without creating bias in the sample. Finally, non-systematic measurement error in the IRIS data resulted in consistently negative IRIS-based studies. This prevented the dissertation from controlling for the effects of lengthened training times, and from addressing important questions about differences across training specialties.

10.3 Further Research

Changes mandated by the Balanced Budget Act have created a natural experimental setting for examining the role of reimbursement incentives in hospital GME sponsorship. The study questions posed by this dissertation should be addressed by tracking changes in sponsorship before and after the regulatory changes. Further descriptive and analytic work is also needed document training decisions in recent years, when market signals regarding potential physician surplus are identifiable and more likely to have influenced the supply of new post-graduate trainees.

11 Appendices

11.1 Variable Construction & Editing

11.1.1 Intern & Resident FTEs

11.1.2 Average & Marginal GME Payment Per Resident FTE

11.1.3 Location & Market Variables

11.1.4 Procedures for Missing and Out-of-Range Values

11.2 IRIS Files

11.2.1 Editing Algorithms and FTE Calculations

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11.3.2 Expansion Models, HCRIS Sample

11.3.3 Expansion Models, IRIS Sample

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11.1 Variable Construction & Editing

11.1.1 Intern & Resident FTEs

Review of Alternative Sources and Definitions for Full Time Equivalents

Resident FTEs can be measured as total FTEs sponsored by the institutions, total claimed for Direct Medical Education payments (DME) or total claimed for Indirect Medical Education payments (IME). Different sources can be used to derive different combinations of these figures, either directly or in the form of the payment claimed (which can be used to derive the number claimed). Not all sources are available for all years. The chart below summarizes FTE data as found in the sources available to me at the time of writing.

	Cost Report Elements on HCRIS			
	Worksheet S-3 (statistics)	Worksheet E/A (pm't settlement)	PSF Files	IRIS Files
For PPS 1–5 :				
Total FTEs on-site	Reported directly	—	Not Available	Not Available
Eligible for IME	Reported directly	Derived, indirectly	Not Available	Not Available
Eligible for DME	Not Applicable	Derived, indirectly	Not Available	Not Available
For PPS 6-10:				
Total FTEs on-site	Reported directly	—	—	Derived
Eligible for IME	Reported directly	Derived, directly	reported directly	Derived
Eligible for DME	—	Derived, directly	—	Derived
For PPS 11:				
Total FTEs on-site	Reported directly	—	—	Derived
Eligible for IME	Reported directly	Derived, directly	reported directly	Derived
Eligible for DME	—	Reported directly	—	Derived
For PPS 12:				
Total FTEs on-site	Reported directly	—	—	Not Available
Eligible for IME	Reported directly	Derived directly	reported directly	Not Available
Eligible for DME	—	Reported directly	—	Not Available

"Not available" indicates that the files are not available for this period. "Not applicable" means that the regulations did not identify FTEs in this manner, in this period. A dash — indicates that the FTE count cannot be determined form this source in this period. "Derived, directly" and "derived, indirectly" are defined below.

FTE data on the S-3 worksheet of the cost report are provided for informational purposes only, and do not flow directly to a cost or payment calculation. As such they are reviewed less carefully more likely to contain inconsistencies in reporting from year to year. In particular, the "Total FTEs" recorded on S-3 sometimes includes residents who are sponsored by the reporting institution, but who are rotating to other clinical sites.

FTEs that are "derived" from payment data on E/Part A worksheet of the cost report have been computed by backing into the FTE portion of the applicable payment formulas, as follows:

- Derived DME FTE =
  DME payments/[(average per-resident amount) ×(mcare days/total non-nursery days)]

  Or, total on-site FTEs can be used as a close proxy for the FTEs eligible for DME payment.

- "Directly Derived" IME FTEs are computed by multiplying the intern-resident bed ratio by the number of acute-care beds. The intern-resident bed ratio is algebraically derived from the IME formula in effect for the period, assuming that the IME adjustment rate is known from the payment data. For PPS 6-12 period, for example:

  Define:
  IRB ≡ Residents/Acute Care Beds
  A ≡ IME Adjustment Rate = IME Payment/(DRG payment+outliers)

  $$1.89\ [(1+IRB)^{.405} - 1) = A$$
  $$(1+IRB)^{.405} - 1) = (A \div 1.89)$$
  $$(1+IRB)^{.405} = [(A \div 1.89) + 1] = A^*$$
  $$.405 \times (\log(1+IRB)) = \log(A^*)$$
  $$\log(1+IRB) = [\log(A^*) \div .405] = A^{**}$$
  $$1+IRB = \exp(A^{**})$$
  $$IRB = \exp(A^{**}) - 1$$

  Then: IME FTE = IRB × # of acute care beds

The Provider-Specific Files (PSF), available after PPS 6, also report the IRB ratio as used by HCFA to compute the interim payments for claims submitted by each provider. This is an interim rate, however, subject to provider correction at the time of cost report filing and intermediary correction at the time of cost report review or audit. Examination of multiple years of PSF data revealed that the interim rates for IME adjustment are often not updated from year to year, even though the filed cost reports generate payment settlements that are based on significantly different ratios. PSF were therefore rejected as a source for IME FTE counts.

- "Indirectly Derived" IME FTEs: Between PPS 1 and PPS 5, the IME adjustment rate is not known because the amount reported as "DRG payment" on the HCRIS files is actually a blend of federal DRG amounts plus the hospital's updated historical amount per discharge. IME payments are computed only on the federal portion of the blend, but that amount is not recorded on HCRIS files.

  Three options for deriving the IME adjustment during this period are available:

  1. The actual DRG amount can be computed by applying all regional and inflationary adjustments to the 1981 federal standardized rate, then multiplying by the transfer-adjusted case mix index for that provider, for each year.

  2. The blended DRG amount can be assumed to represent an approximation of the total federal rate, and the IME adjustment can be estimated by simpy adusting the DRG amount by that year's applicable blend percent, as follows:

     Phase-in IME Adjustment Rate =
     A' = IME payments / [("DRG" + Outliers) × blend %]

     The IRB and IME FTE are then algebraically derived in the same way as described above for PPS 6-12, but using the IME payment formula appropriate to the year.

  3. The resident FTEs reported on the statistics page, identified as rotating in the acute-care section of the hospital, can be used to estimate the applicable IRB as well as the IME Adjustment. After the IME Adjustment is computed, it can be used to derive the federal portion of the blended DRG amount, which can then be examined for consistency with later payment data.

Appendix 1.1

The necessary case mix or regional input price adjusters were not available to make the computation for the first method. Methods 2 and 3 were both applied and the results were compared within hospital for year-to-year consistency with later periods. Method 2 presented greater potential for bias, related to the extent to which the hospital's historical cost per discharge exceeded or was less than the federal standardized cost. The third option was used for all analyses in this dissertation.

11.1.2 Average and Marginal GME Payments per Resident FTE

Variable Calculations, Expansion Model

Marginal IME payments received for the next resident hired:

Step 1: compute "marginal IRB ratio" = IRB' equal to the (FTE+1) / # beds

Step 2: compute the IME adjustment applicable to the appropriate PPS year, using IRB'

Step 3: subtract the IME adjustment computed from the data, from the IME adjustment computed from IRB'. Difference represents the marginal amount received for the next resident.

For PPS 5–12:
marginal adj/FTE = $[1.89\times((1+IRB')^{.405}-1)]-[1.89\times((1+IRB)^{.405}-1)]$

For PPS 4–5:
marginal adj/FTE = $[2.00\times((1+IRB')^{.405}-1)]-[2.00\times((1+IRB)^{.405}-1)]$

For PPS 1–3:
marginal adj/FTE = $[10\times .1157\times IRB'] - [10\times .1157\times IRB)$

Note that PPS years 1 through 3 use a linear formula to computing IME payments. Therefore marginal adjustment = average adjustment.

Step 4: Multiply the results from Step 3 times the total (DRG + Outlier) amounts received for each hospital.

During PPS 5 through 12 the marginal IME payment per resident is equal to the marginal adjustment × (DRG$ + Outlier$). During the PPS phase-in period, however, a judgement must be made in choosing the appropriate DRG payment amount to use for modeling purposes.

An argument could be made that hospital management was aware of the phase-in schedule from the first year, so we should assume that they responded to the incentives created by the formula based on its final impact after the phase-in. If the amount is

"grossed up" to reflect the amount that would have been payable under 100% PPS rates, however, the marginal payment drops significantly in PPS 4 in response to regulatory changes. The decrease has a significant effect on the model, yielding a strong negative coefficient on the marginal payment variable when it is interacted on the pre-PPS phase-in time indicator.

If the DRG amount is left unchanged, so that it reflects the IME amount received on the federal portion of the blended rate, there is a pronounced trend of increased marginal IME payments between PPS 1 and PPS 3 resulting from the progression of the phase-in period. Then, in PPS 4, the last phase-in effect is masked by the payment formula change. Overall, however, the resulting secular increases in the payment variable have the effect of increasing the model's predicted association between marginal payments and FTE change.

Finally, the DRG payments could be grossed up to reflect the DRG amounts payable under the 100% federal period, but the IME adjustment could be recomputed using a consistent formula (e.g., the formula in effect for the PPS 6–12). In this manner, the marginal IME variable would be partially stabilized over time. In some ways this specification serves the model best, in that variations in the marginal IME payments received can be considered a better reflection of differences within and between hospitals that result from differences in Medicare utilization, case mix intensity and teaching intensity. The specification is difficult to defend, however, on the basis that hospital management had no way of knowing, between PPS years 1 and 5, what the "reimbursement return" was going to be under a formula that was not legislated until 1987.

There is no good solution to the problem of defining marginal IME payments through PPS 5. The first two options create year-to-year patterns that generate potentially spurious correlation, and the third is a questionable operationalization of the conceptual model that attempts to assess the influence of reimbursement on hospital decisions. For this dissertation I tested the effects of all three approaches, and chose to use the second, as the measure that most closely reflects the actual financial transactions of the period. I then included interaction terms on PPS 2 and on the period PPS 3-5, to try to isolate the distorting effects of both the phase-in schedule and the regulatory changes.

Appendix 1.2

Marginal and Average DME Payments per Resident Hired:

Average and marginal DME payments per resident are equal; the terms are used interchangeably.

DME payments prior to PPS year 6 were computed as part the hospital's "cost pass-through". Most HCRIS records since PPS 2 have been restated, in order to separate the direct medical education pass-through from the capital and other pass-throughs. A significant minority of hospitals shows DME payments of zero in the early years, however, indicating that the payments were not recomputed on those records (less that 5% of teaching hospitals literally do not receive any DME amounts). The DME variable is therefore subject to substantial reporting error in the early years. Model results are significantly modified when the zero-payment providers are excluded from the estimation sample, compared to when they are included as observations with a zero-value in the variable, or when the DME amount is excluded from the model altogether.

An optional marginal payment variable was investigated (marginal GME per resident), that sums both the IME and DME marginal payment amounts. Although this is theoretically the best variable for the Expansion Model because it reflects what hospital managers would be expected to identify as their reimbursement return on adding a resident, the measurement error contributed by the "zero" values in the early years is problematic. Model results using the combined marginal GME payment variable were different in significance and sign for the early years. For the later period, they were qualitatively similar to results from the model using only IME payments, but the strength of the effect was smaller.

To minimize the effect of measurement error, the final model is based on marginal IME payments only. However, overall conclusions would not be altered if the total GME payment variable were used instead.

Variable Calculations, Conversion Model

Potential IME Payments per Resident:

Potential IME payments per resident were computed based on a fixed number of residents (3.0 FTE), using the PPS 6-12 formula and applying the number of beds, Medicare utilization and DRG payments applicable in the base year of the observation period, as follows:

$$\text{Potential IME adjustment} = [1.89 \times (1 + (3 \div \#\text{beds}))^{.405} - 1]$$
$$\text{Potential IME per Resident} = [\text{Potential IME adjustment} \times (\text{DRG\$} + \text{Outlier\$})] \div 3$$

For reasons explained in Appendix 1.1, the DRG amounts in PPS 1 had to be imputed using information from the number of residents and the IME payment amounts. An alternative computation, for the model estimating 12-year probability of conversion, used hospital beds and DRG payment amounts as of PPS 6 instead of PPS 1. No differences in model results were detected from this alternative specification, however, providing no evidence of model bias attributable to the process of imputing Year 1 amounts. The PPS Year 1-based IME variable was used for the final model

11.1.3 Location & Market Variables

Number of Competitors:

Hospital location was determined by the hospital zip code. Competitors were identified as short-term acute care facilities located within a 15-mile radius of the zip code centroid, that were participating Medicare hospitals paid under the PPS/DRG system. Thus, neighboring long-stay, cancer, children's, psychiatric and rehab facilities were not included in the count.

Number of competitors was computed separately for each year of data. Dummy records were added in any years where a hospital showed a gap in cost reports, on the assumption that a break in reporting is more likely than a break in operations.

Distance to Nearest Major Teaching Hospital

Major teaching hospital is defined as a member of the Council of Teaching Hospitals, with membership identified as of PPS 12, from the AHA Hospital survey. Thus, a hospital that became a COTH member at the end of the study period would be identified as a major teaching facility throughout the study period (provided it engaged in teaching activity throughout the period).

Distances were measured from the centroid of the hospital zip code. A distance of –0– indicates that a major teaching facility is located in the same zip code.

Distance from the nearest teaching facility was computed separately for each year of data. Dummy records were added in any years where a hospital showed a gap in cost reports, on the assumption that a break in reporting is more likely than a break in operations.

Physician Supply

Physician supply was measured at the county level, using the number of practicing physicians and county population, as reported in the Area Resource Files. Numerator and denominator data for missing years were interpolated, prior to computing the ratio.

11.1.4 Procedures for Missing and Out-of-Range Variables

HCRIS data were subject to intense review for out-of-range values. Consistency checks were accomplished by computing year-to-year changes on all continuous variables used directly or indirectly in the model. Consistency was also examined by computing standard ratios including average length of stay, cost per case, payment per case, payment per day, and assessing the reasonableness of their changes over time, within unique facility.

For values other than the dependent variable, clearly out-of-range values were replaced by missing data points, and the series was interpolated (within hospital) to create replacement values.

In PPS 1, the number of routine acute care beds was not reported. The values were derived using a set of decision rules that took into account PPS 2 changes in critical care beds and total facility beds (a measure that includes psychiatric, rehab and long-term care beds, and is not used elsewhere in the analysis). For the remaining subset (less than 15%) of hospitals whose acute care capacity in PPS 1 could not be definitely identified by these rules, the number of acute care beds was modeled as a function of other types of capacity and trends over time in hospitals of similar characteristics.

Of all data included in the HCRIS files, the financial statement information used to derive total operating margins was the most error-prone. Many facilities were inconsistent about signing revenue deductions, and many recorded total expenditure data on the financial statement section that did not tie to the total from the trial balance of expenditures that is used in the computation of Medicare costs. Out of range values for the computed total margin were replaced by imputed values, but the proportion of missing or unusable data was so great that the series was also subject to extrapolation (extending interpolated values to either "end" of the individual hospital series) as well. Extrapolated values in excess of 0.99 or below –0.99 were truncated at those values. (Prior investigation revealed no records, out of the nearly 65,000 in the study sample, with margins outside of this range, that did not have obvious errors in the net revenue or expense calculation.)

Appendix 1.4

Disproportionate share hospitals are only identified after PPS 5, and their component disproportionate share index values are only available from the PSF data, which is available after PPS 6. Several hospitals were missing from the PSF, or were in operation during the initial five years of the study period but not after PPS 6. A hospital with no source for DSH index values was excluded from the estimation sample. DSH index values for the period prior to and including PPS 5 were derived based on their levels at PPS 6, resulting in a non-time varying variable for the first half of the study period.

11.2 IRIS File Documentation

11.2.1 File Lay-out, Editing Algorithms & FTE Calculations

General Information:

Interns & Residents Information System files (IRIS)

From SAS file, created from HCFA tapes for 1989 through 1995 (6 years, one file per year).

One record = one resident's set of rotations at one provider in one year.

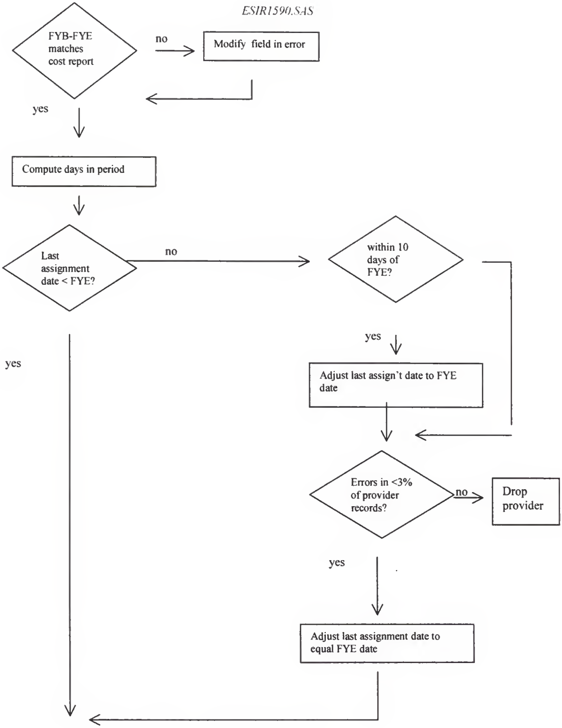
Resident ID # have been removed.

Descriptions and commentary on all file variables as received from HCFA are included in the table below. They are followed with a schematic of the edit algorithms.

IRIS Files, as Received from HCFA:

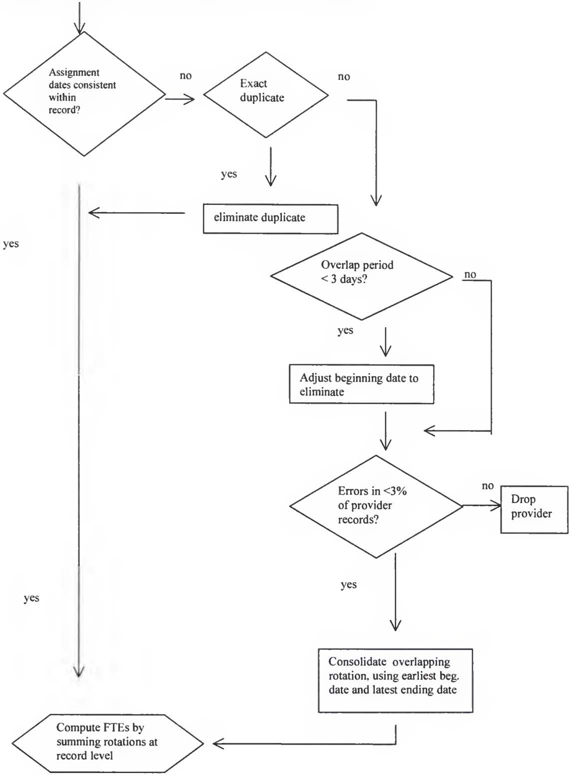
variable name	Description	Comments
1. PROVNUM	HCFA provider number	
2. FYEND	provider's fiscal year end	*Also reflects the end of cost reporting period*
3. FYINT	fiscal intermediary number	*Also appears on HCFA cost report file for match.*
4. FYBEG	provider's fiscal year beginning	
5. RESCODEC	residency specialty code	
6. RESDESC	residency specialty description	
7. PGY	post graduate year of training (range = 0 – 9)	*Providers using "PGY0" for 1st year identified and converted to obtain a consistent classification, beginning "PGY1"*
8. EMPLNAME	Name of facility that employs the resident.	*Not necessarily the same as the provider. Affiliated teaching hospitals that are not independent match sites will show different employers. User-entry field, not standard*
9. MSCODEC	5-digit identifying code for medical school from which resident graduated.	*International schools (except Canada) are all coded the #9999.*
10. GRADMONC 11. GRADYRC	Med school graduation - month Med school graduation - year	
12. IMECNTC	FTE status from Sept 1 count for IME Adjustment	*Not used after 1989-90 (Yr 6). Sept 1 headcount was replaced by 12-mo average*
13. FRGNMSCH	Foreign medical school graduate (Y/N)	
14. FMCMONC 15. FMCYRC	FMGEMS -- pass date, month FMGEMS -- pass date, year	*Only applicable if item 13 is "Y"*
16. RECYRS 17. RECMONC 18. RECDAYC	Record creation date - year record creation date - month record creation date - day	*Refers to IRIS records.*
19. PPSC	PPS indicator (0/1)	*1 if a DRG provider (with or without exempt sub-providers);* *0 if primary facility is exempt (TEFRA or cost)*
20. ASSGNCNT	Assignment count: number of different rotation assignments for this individual resident at this individual provider	*Can be up to twenty different assignments.*
Assignment data:		
21. ASSBEG1 22. ASSEND1	1st assignment: start date 1st assignment: end date	*Format is YRDAY --- used to compute elapsed days*
23. FPTPER1	full time equivalency (* 100) for that period assignment	*Should be used to indicate part time employment (e.g. shared resident slots for parental leave) but appeared inconsistent. Some providers use to eliminate multiple records per resident; decision rule established to identify these providers and adjust FTEs only in these cases*
24. IMEPER1	% 1st assignment time that is eligible to be counted for IME Adustment (*100)	*Range 0 to 100 -- 0 if resident is on an exempt unit or offsite or not assigned to patient care but can be prorated for mixed schedules*
25. GMEPER1	% 1st assignment time that is eligible to be counted for DME Adjustment (* 100)	*Note this does not include the adjustment for weighting FTE by .50 for years after the initial residency period or greater than PGY5.*
26 -30	same items, for 2nd assignment if applicable	
31 ---	same items, for 3rd- 20th assignments if applicable	

Period Beginning/Ending Date Consistency:



Continue to assignment date edits...

Beginning/Ending Rotation Assignment Date Consistency:



Full Time Equivalents Calculations & Analysis Files:

By assignment period, create the following:

FTEPER* = [# days in assignment* / # days in total period] * PTSTATUS(see below)
IMEFTE* = IMEPER* x FTEPER*
DMEFTE* = DMEPER* x FTEPER*
FMGWGHT= 1 if FRGNMSCH=1 & MCYRC<FYEND; 0 if not
SPECWGHT=1.0 or 0.5, according to attached table

Within record, ΣFTEPER*, ΣIMEFTE* and ΣDMEFTE* creates unweighted full time equivalency variables by resident within hospital. Save as TOTFTE, DMEFTE & IMEFTE

Within hospital, create variable "DMECHK" equal to

- Σ[ΣDMEFTE* x FMGWGHT x SPECWGHT]

This should tie to total FTEs claimed for direct medical education payment, to be verified against field f478b & c in PPS 10-12 cost reports.

"PTSTATUS": Edits regarding poviders' use of FPTPER* input field:
Field designating full or part-time status of resident is inconsistnetly used by providers. Majority of those not entering 1.00 entered numbers reflecting same proportions as appear in IMEPER* or DMEPER* . FPTPER* should be exluded from FTE calculations. "PTSTATUS" should be derived from FPTPER* according to the following rules:

- If FPTPER* is 0.5 when neither IMEPER* nor DMEPER* is 0.5 assume this is a true "shared" residency slot: PTSTATUS = 0.5; else PTSTATUS = 1.00
- If FPTPER* is not 1.00 and there is only one assignment period; and the beginning and ending dates correspond to FYBEG and FYEND. These are presumed to be hospitals that summarized their rotations prior to IRIS data entry and are using the FPTPER* field to account for proportions of time spent off-site or in non-allowable activities; set PTSTATUS = FPTPER*.

Analysis Files:
File 1: TOTFTE, DMEFTE, IMEFTE, DMECHK, in total, summary statistics by hospital
File 2: TOTFTE, DMEFTE, IMEFTE, by RESCODEC.
File 3: TOTFTE, DMEFTE, IMEFTE, by FRGNMSCH status
File 4: TOTFTE, DMEFTE, IMEFTE, by PGY

APPENDIX 2.2

11.2.2 IRIS File Edit Summary, As Generated from SAS Files, June 1998

PPS Yr		# Records	%	# Providers	# Providers, SAS Analysis Files	%
6	original number	124,379	100.0%		1,008	100.0%
	FY date errors	(855)	-0.7%	(10)	(10)	-1.0%
	>3% overlap	(788)	-0.6%	(5)	(5)	-0.5%
	remaining	122,736	98.7%		993	98.5%
7	original number	158,016	100.0%		1,210	100.0%
	FY date errors	(927)	-0.6%	(6)	(6)	-0.5%
	>3% overlap	(313)	-0.2%	(6)	(6)	-0.5%
	remaining	156,776	99.2%		1,198	99.0%
8	original number	164,255	100.0%		1,216	100.0%
	FY date errors	(1,513)	-0.9%	(5)	(5)	-0.4%
	>3% overlap	(536)	-0.3%	(6)	(6)	-0.5%
	remaining	162,206	98.8%		1,205	99.1%
9	original number	147,457	100.0%		1,102	100.0%
	FY date errors	(1,219)	-0.8%	(4)	(4)	-0.4%
	>3% overlap	(3,453)	-2.3%	(14)	(14)	-1.3%
	remaining	142,785	96.8%		1,084	98.4%
10	original number	149,488	100.0%		1,079	100.0%
	FY date errors	(202)	-0.1%	(1)	(1)	-0.1%
	>3% overlap	(2,325)	-1.6%	(13)	(13)	-1.2%
	remaining	146,961	98.3%		1,065	98.7%
11	original number	123,098	100.0%		832	100.0%
	FY date errors	-	0.0%	-	-	0.0%
	>3% overlap	(978)	-0.8%	(12)	(12)	-1.4%
	remaining	122,120	99.2%		820	98.6%
	original number	866,693	100.0%		6,447	100.0%
	FY date errors	(4,716)	-0.5%		(26)	-0.4%
	>3% overlap	(8,393)	-1.0%		(56)	-0.9%
	remaining	853,584	98.5%		6,365	98.7%
	edit check	853,584			6,365	

11.3 Regression Tables

11.3.1 Longitudinal Study of IME Costs

Regression 1: Dependent Variable = Nominal Average Medicare Operating Cost/Discharge
WLS w/ Huber-White Standard Errors, Clustering by Provider
Weight = Medicare Discharges

```
Regression with robust standard errors                 Number of obs =    35099
                                                       F( 18,  5416) = 1250.46
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.7718
Number of clusters (provider) = 5417                   Root MSE      =  .16405
```

lnopcstl	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
lnIRBX	.5545805	.0419568	13.218	0.000	.4723284	.6368327
lncmih	.9450668	.0218326	43.287	0.000	.9022662	.9878675
lnwage	.6089261	.0164229	37.078	0.000	.5767306	.6411217
lnbeds	.0657549	.0045918	14.320	0.000	.0567531	.0747566
urban	.0638254	.0069489	9.185	0.000	.0502028	.077448
yr7	.085697	.0038926	22.015	0.000	.078066	.0933281
yr8	.1375219	.0058652	23.447	0.000	.1260238	.1490199
yr9	.1560547	.0040149	38.869	0.000	.1481839	.1639255
yr10	.1623359	.0042474	38.220	0.000	.1540092	.1706626
yr11	.1339171	.0046746	28.648	0.000	.1247529	.1430813
yr12	.1152171	.0048239	23.885	0.000	.1057604	.1246739
DSH	.0148695	.0047466	3.133	0.002	.0055643	.0241748
IRBX7	-.0310178	.0302603	-1.025	0.305	-.0903401	.0283046
IRBX8	-.0838161	.0378056	-2.217	0.027	-.1579302	-.0097019
IRBX9	-.1580276	.0335323	-4.713	0.000	-.2237644	-.0922908
IRBX10	-.1664803	.0351773	-4.733	0.000	-.2354419	-.0975187
IRBX11	-.2064411	.0364173	-5.669	0.000	-.2778336	-.1350486
IRBX12	-.233911	.0378859	-6.174	0.000	-.3081826	-.1596395
_cons	7.757347	.0199316	389.198	0.000	7.718273	7.796421

linear combinations on interacted effects:

lnopcstl	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
lnIRBX + IRBX7 = 0.0	.5235628	.0307035	17.052	0.000	.4633715	.583754
lnIRBX + IRBX8 = 0.0	.4707645	.0310959	15.139	0.000	.409804	.531725
lnIRBX + IRBX9 = 0.0	.3965529	.0288291	13.755	0.000	.3400364	.4530695
lnIRBX + IRBX10= 0.0	.3881002	.0258848	14.993	0.000	.3373556	.4388449
lnIRBX + IRBX11= 0.0	.3481394	.0266695	13.054	0.000	.2958565	.4004223
lnIRBX + IRBX12= 0.0	.3206695	.0256797	12.487	0.000	.270327	.3710121

Appendix 3.1

Regression 2: Dependent Variable = Nominal Average Medicare Operating Cost/Discharge
WLS w/ Huber-White Standard Errors, Clustering by Provider
Weight = Medicare Discharges
Includes Interaction on DSH Provider Status

Regression with robust standard errors	Number of obs = 35099
	F(19, 5416) = 1202.57
	Prob > F = 0.0000
	R-squared = 0.7725
Number of clusters (provider) = 5417	Root MSE = .1638

lnopcstl	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
lnIRBX	.4301104	.0537129	8.008	0.000	.3248116	.5354093
lncmih	.9477354	.0217973	43.479	0.000	.9050039	.9904669
lnwage	.6100517	.0164365	37.116	0.000	.5778295	.6422738
lnbeds	.0673577	.0046249	14.564	0.000	.0582911	.0764243
urban	.065057	.0069769	9.325	0.000	.0513795	.0787345
yr7	.0866238	.0038997	22.213	0.000	.0789789	.0942688
yr8	.1387897	.0059125	23.474	0.000	.1271988	.1503806
yr9	.1578598	.0040459	39.017	0.000	.1499282	.1657915
yr10	.1643804	.0042751	38.451	0.000	.1559996	.1727612
yr11	.1362764	.0047164	28.894	0.000	.1270303	.1455224
yr12	.1176334	.0048705	24.152	0.000	.1080852	.1271815
DSH	**.004604**	**.0049981**	**0.921**	**0.357**	**-.0051943**	**.0144022**
IRBXDSH	**.1844296**	**.0488324**	**3.777**	**0.000**	**.0886984**	**.2801609**
IRBX7	-.0469182	.030768	-1.525	0.127	-.1072359	.0133994
IRBX8	-.1048489	.0384738	-2.725	0.006	-.1802731	-.0294248
IRBX9	-.1866525	.0346	-5.395	0.000	-.2544824	-.1188226
IRBX10	-.1985064	.0356485	-5.568	0.000	-.2683918	-.128621
IRBX11	-.2397147	.0369852	-6.481	0.000	-.3122206	-.1672087
IRBX12	-.2670013	.0380067	-7.025	0.000	-.3415097	-.1924929
_cons	7.75121	.0200563	386.473	0.000	7.711892	7.790529

linear combinations on interacted effects:

lnopcstl	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
on non-DSH providers:						
lnIRBX + IRBX7 = 0.0	.3831922	.0475245	8.063	0.000	.2900251	.4763593
lnIRBX + IRBX8 = 0.0	.3252615	.0499132	6.517	0.000	.2274116	.4231114
lnIRBX + IRBX9 = 0.0	.2434579	.0488319	4.986	0.000	.1477277	.3391881
lnIRBX + IRBX10 = 0.0	.231604	.0487439	4.751	0.000	.1360463	.3271617
lnIRBX + IRBX11 = 0.0	.1903958	.050483	3.771	0.000	.0914288	.2893628
lnIRBX + IRBX12 = 0.0	.631091	.0488278	3.340	0.001	.0673871	.2588311
on DSH providers:						
lnIRBX + IRBXDSH = 0.0	.6145401	.0433746	14.168	0.000	.5295084	.6995717
lnIRBX + IRBXDSH + IRBX7 = 0.0	.5676218	.0319085	17.789	0.000	.5050684	.6301753
lnIRBX + IRBXDSH + IRBX8 = 0.0	.5096911	.0324669	15.699	0.000	.446043	.5733393
lnIRBX + IRBXDSH + IRBX9 = 0.0	.4278875	.0295648	14.473	0.000	.3699286	.4858465
lnIRBX + IRBXDSH + IRBX10= 0.0	.4160337	.026761	15.546	0.000	.3635714	.4684959
lnIRBX + IRBXDSH + IRBX11= 0.0	.3748254	.0267086	14.034	0.000	.3224658	.427185
lnIRBX + IRBXDSH + IRBX12= 0.0	.3475387	.0261865	13.272	0.000	.2962027	.3988748

Regression 3: Dependent Variable = Nominal Average Medicare Operating Cost/Discharge
WLS w/ Huber-White Standard Errors, Clustering by Provider

Appendix 3.1

Weight = Medicare Discharges
Includes Interaction on COTH member Status

Regression with robust standard errors

Number of obs = 35099
F(19, 5416) = 1161.35
Prob > F = 0.0000
R-squared = 0.7716
Root MSE = .16409

Number of clusters (provider) = 5417

lnopcst1	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
lnIRBX	.5065354	.0577109	8.777	0.000	.3933988	.6196721
lncmih	.9415152	.0218978	42.996	0.000	.8985867	.9844437
lnwage	.6044439	.0164119	36.830	0.000	.57227	.6366179
lnbeds	.0692273	.0046505	14.886	0.000	.0601104	.0783441
urban	.0677993	.0069589	9.743	0.000	.0541571	.0814415
yr7	.0870584	.0037973	22.926	0.000	.0796142	.0945027
yr8	.1393042	.0057507	24.224	0.000	.1280304	.1505779
yr9	.1591222	.0037749	42.152	0.000	.1517218	.1665226
yr10	.165936	.0039873	41.616	0.000	.1581192	.1737528
yr11	.1380646	.0044254	31.198	0.000	.1293889	.1467402
yr12	.1196656	.0045497	26.302	0.000	.1107464	.1285848
coth	**-.0281302**	**.0152877**	**-1.840**	**0.066**	**-.0581002**	**.0018398**
IRBXcoth	**.1434882**	**.0659496**	**2.176**	**0.030**	**.0142004**	**.272776**
IRBX7	-.0343544	.0305784	-1.123	0.261	-.0943004	.0255917
IRBX8	-.0898313	.0383917	-2.340	0.019	-.1650945	-.0145682
IRBX9	-.166502	.0339798	-4.900	0.000	-.2331161	-.099888
IRBX10	-.1787671	.0361969	-4.939	0.000	-.2497276	-.1078065
IRBX11	-.2219998	.0377468	-5.881	0.000	-.2959987	-.1480009
IRBX12	-.24996	.0389565	-6.416	0.000	-.3263305	-.1735895
_cons	7.742105	.0200579	385.987	0.000	7.702783	7.781426

linear combinations on interacted effects:

lnopcst1	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
on non-COTH members:						
lnIRBX + IRBX7 = 0.0	.4721811	.0530914	8.894	0.000	.3681006	.5762616
lnIRBX + IRBX8 = 0.0	.4167041	.0555421	7.502	0.000	.3078193	.5255889
lnIRBX + IRBX9 = 0.0	.3400334	.0515804	6.592	0.000	.2389151	.4411517
lnIRBX + IRBX10 = 0.0	.3277684	.0514879	6.366	0.000	.2268314	.4287054
lnIRBX + IRBX11 = 0.0	.2845357	.0517421	5.499	0.000	.1831003	.385971
lnIRBX + IRBX12 = 0.0	.2565754	.0512313	5.008	0.000	.1561416	.3570093
on COTH members:						
lnIRBX + IRBXcoth = 0.0	.6500236	.0596498	10.897	0.000	.533086	.7669613
lnIRBX + IRBXcoth+IRBX7 = 0.0	.6156693	.0498985	12.338	0.000	.5178482	.7134903
lnIRBX + IRBXcoth+IRBX8 = 0.0	.5601923	.0473234	11.838	0.000	.4674193	.6529653
lnIRBX + IRBXcoth+IRBX9 = 0.0	.4835216	.04694	10.301	0.000	.3915003	.5755429
lnIRBX + IRBXcoth+IRBX10= 0.0	.471256	.043179	10.914	0.000	.3866083	.5559048
lnIRBX + IRBXcoth+IRBX11= 0.0	.4280239	.0427999	10.001	0.000	.3441188	.5119289
lnIRBX + IRBXcoth+IRBX12= 0.0	.4000636	.0426229	9.386	0.000	.3165057	.4836216

Appendix 3.1

Regression 4: Dependent Variable = Nominal Average Medicare Operating Cost/Discharge Adjusted to Remove DSH and Outlier Payments
WLS w/ Huber-White Standard Errors, Clustering by Provider
Weight = Medicare Discharges

```
Regression with robust standard errors                 Number of obs =   35091
                                                       F( 18,  5416) =  923.37
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.6920
Number of clusters (provider) = 5417                   Root MSE      =  .18061
```

lnopcst6	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
lnIRBX	.4697676	.0463902	10.126	0.000	.3788242	.560711
lncmih	.9718616	.0247085	39.333	0.000	.923423	1.0203
lnwage	.5108222	.0199235	25.639	0.000	.471764	.5498803
lnbeds	.05683	.0052469	10.831	0.000	.0465439	.067116
urban	.0606565	.0075387	8.046	0.000	.0458777	.0754354
yr7	.0895464	.0039625	22.598	0.000	.0817783	.0973146
yr8	.1491695	.0059235	25.183	0.000	.137557	.160782
yr9	.1652751	.0041488	39.837	0.000	.1571418	.1734084
yr10	.1678618	.0044424	37.786	0.000	.159153	.1765707
yr11	.1340088	.0049364	27.147	0.000	.1243316	.1436861
yr12	.1011663	.0052819	19.153	0.000	.0908116	.111521
DSH	-.0948464	.0050555	-18.761	0.000	-.1047571	-.0849357
IRBX7	-.0180272	.0338355	-0.533	0.594	-.0843585	.048304
IRBX8	-.0604913	.0423038	-1.430	0.153	-.1434237	.0224411
IRBX9	-.1559142	.038326	-4.068	0.000	-.2310486	-.0807798
IRBX10	-.1633355	.041456	-3.940	0.000	-.244606	-.082065
IRBX11	-.2311819	.0438179	-5.276	0.000	-.3170826	-.1452811
IRBX12	-.2645307	.0473302	-5.589	0.000	-.357317	-.1717445
_cons	7.763937	.022094	351.404	0.000	7.720624	7.80725

linear combinations on interacted effects:

lnopcst6	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
lnIRBX + IRBX7 = 0.0	.4517404	.0359822	12.555	0.000	.3812009	.5222799
lnIRBX + IRBX8 = 0.0	.4092763	.0353545	11.576	0.000	.3399673	.4785854
lnIRBX + IRBX9 = 0.0	.3138535	.0335509	9.355	0.000	.2480803	.3796266
lnIRBX + IRBX10= 0.0	.3064321	.029981	10.221	0.000	.2476573	.365207
lnIRBX + IRBX11= 0.0	.2385858	.0326736	7.302	0.000	.1745324	.3026392
lnIRBX + IRBX12= 0.0	.2052369	.03371	6.088	0.000	.1391517	.2713221

Regression 5: Dependent Variable = Nominal Average Medicare Operating Cost/Discharge Adjusted to Remove DSH and Outlier Payments
WLS w/ Huber-White Standard Errors, Clustering by Provider,
Weight = Medicare Discharges
Includes Interaction on DSH Status

Regression with robust standard errors

Number of obs =	35091
F(19, 5416) =	882.78
Prob > F =	0.0000
R-squared =	0.6920
Root MSE =	.18059

Number of clusters (provider) = 5417

lnopcst6	Robust Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
lnIRBX	.4310473	.0563235	7.653	0.000	.3206306	.5414639
lncmih	.9726926	.0246444	39.469	0.000	.9243797	1.021006
lnwage	.5111719	.0199506	25.622	0.000	.4720608	.550283
lnbeds	.0573286	.0053094	10.798	0.000	.04692	.0677372
urban	.0610395	.0075553	8.079	0.000	.0462281	.075851
yr7	.0898346	.0039673	22.644	0.000	.0820572	.0976121
yr8	.1495639	.0059601	25.094	0.000	.1378797	.1612482
yr9	.1658367	.0041711	39.758	0.000	.1576596	.1740138
yr10	.1684978	.0044675	37.716	0.000	.1597397	.1772559
yr11	.1347425	.0049686	27.119	0.000	.1250021	.144483
yr12	.1019177	.0053074	19.203	0.000	.091513	.1123224
DSH	**-.09804**	**.0054608**	**-17.953**	**0.000**	**-.1087455**	**-.0873346**
IRBXDSH	**.0573727**	**.050741**	**1.131**	**0.258**	**-.0421**	**.1568455**
IRBX7	-.0229732	.0334214	-0.687	0.492	-.0884925	.0425461
IRBX8	-.0670343	.0420218	-1.595	0.111	-.1494138	.0153453
IRBX9	-.164819	.0378672	-4.353	0.000	-.239054	-.090584
IRBX10	-.1732983	.0409899	-4.228	0.000	-.2536549	-.0929417
IRBX11	-.2415321	.0432644	-5.583	0.000	-.3263477	-.1567165
IRBX12	-.274824	.0464047	-5.922	0.000	-.3657958	-.1838521
_cons	7.762028	.0223127	347.875	0.000	7.718286	7.80577

linear combinations on interacted effects:

lnopcst6	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
on non-DSH providers:						
lnIRBX + IRBX7 = 0.0	.4080741	.0475066	8.590	0.000	.3149421	.5012061
lnIRBX + IRBX8 = 0.0	.364013	.0488603	7.450	0.000	.2682272	.4597988
lnIRBX + IRBX9 = 0.0	.2662283	.0476189	5.591	0.000	.172876	.3595806
lnIRBX + IRBX10 = 0.0	.257749	.0468024	5.507	0.000	.1659974	.3495006
lnIRBX + IRBX11 = 0.0	.1895151	.0487038	3.891	0.000	.0940362	.2849941
lnIRBX + IRBX12 = 0.0	.1562233	.047605	3.282	0.001	.0628983	.2495483
on DSH providers:						
lnIRBX + IRBXDSH = 0.0	.48842	.0493224	9.903	0.000	.3917282	.5851118
lnIRBX + IRBXDSH + IRBX7 = 0.0	.4654468	.0396225	11.747	0.000	.3877707	.5431229
lnIRBX + IRBXDSH + IRBX8 = 0.0	.4213857	.0384336	10.964	0.000	.3460404	.496731
lnIRBX + IRBXDSH + IRBX9 = 0.0	.323601	.0362217	8.934	0.000	.2525919	.3946102
lnIRBX + IRBXDSH + IRBX10= 0.0	.3151217	.0324257	9.718	0.000	.2515543	.3786891
lnIRBX + IRBXDSH + IRBX11= 0.0	.2468879	.0347561	7.103	0.000	.178752	.3150237
lnIRBX + IRBXDSH + IRBX12= 0.0	.213596	.0362308	5.895	0.000	.1425691	.2846229

Regression 6: Dependent Variable = Nominal Average Medicare Operating Cost/Discharge
Adjusted to Remove DSH and Outlier Payments
WLS w/ Huber-White Standard Errors, Clustering by Provider
Weight = Medicare Discharges
Includes Interaction on COTH membership

Regression with robust standard errors

Number of obs = 35091
F(19, 5416) = 807.88
Prob > F = 0.0000
R-squared = 0.6745
Root MSE = .18566

Number of clusters (provider) = 5417

lnopcst6	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
lnIRBX	.2951658	.0678124	4.353	0.000	.1622262	.4281054
lncmih	.9955898	.026559	37.486	0.000	.9435234	1.047656
lnwage	.5540861	.0206722	26.803	0.000	.5135603	.5946119
lnbeds	.046748	.0053452	8.746	0.000	.0362693	.0572267
urban	.0405804	.0078874	5.145	0.000	.0251179	.0560428
yr7	.0814192	.0039875	20.419	0.000	.0736021	.0892363
yr8	.1389504	.0058123	23.906	0.000	.1275559	.1503448
yr9	.1467111	.0040202	36.493	0.000	.1388298	.1545924
yr10	.1472036	.0043057	34.188	0.000	.1387627	.1556445
yr11	.1109504	.0048661	22.800	0.000	.1014108	.12049
yr12	.076627	.0052651	14.554	0.000	.0663053	.0869486
coth	**-.0229918**	**.0190152**	**-1.209**	**0.227**	**-.0602691**	**.0142856**
IRBXcoth	**.1473079**	**.0810232**	**1.818**	**0.069**	**-.0115302**	**.3061459**
IRBX7	-.0202248	.0342448	-0.591	0.555	-.0873583	.0469087
IRBX8	-.0612414	.0424856	-1.441	0.150	-.1445302	.0220474
IRBX9	-.1489694	.0390048	-3.819	0.000	-.2254345	-.0725043
IRBX10	-.1561122	.0413117	-3.779	0.000	-.2370998	-.0751246
IRBX11	-.2179674	.0432084	-5.045	0.000	-.3026732	-.1332615
IRBX12	-.2492108	.0466461	-5.343	0.000	-.340656	-.1577657
_cons	7.809017	.0221589	352.409	0.000	7.765577	7.852458

linear combinations on interacted effects:

lnopcst6	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
on non-COTH members:						
lnIRBX + IRBX7 = 0.0	.274941	.0638077	4.309	0.000	.1498523	.4000298
lnIRBX + IRBX8 = 0.0	.2339245	.0657393	3.558	0.000	.1050489	.3628
lnIRBX + IRBX9 = 0.0	.1461965	.0634291	2.305	0.021	.0218499	.270543
lnIRBX + IRBX10 = 0.0	.1390537	.064231	2.165	0.030	.0131351	.2649722
lnIRBX + IRBX11 = 0.0	.0771985	.0647635	1.192	0.233	-.0497641	.204161
lnIRBX + IRBX12 = 0.0	.045955	.066873	0.687	0.492	-.085143	.177053
on COTH members:						
lnIRBX + IRBXcoth = 0.0	.4424737	.0683575	6.473	0.000	.3084655	.5764819
lnIRBX+IRBXcoth+IRBX7 = 0.0	.4222489	.0604236	6.988	0.000	.3037944	.5407033
lnIRBX + IRBXcoth+IRBX8 = 0.0	.3812323	.05738	6.644	0.000	.2687445	.4937202
lnIRBX + IRBXcoth+IRBX9 = 0.0	.2935043	.0567358	5.173	0.000	.1822792	.4047294
lnIRBX + IRBXcoth+IRBX10= 0.0	.2863615	.052115	5.495	0.000	.1841952	.3885278
lnIRBX + IRBXcoth+IRBX11= 0.0	.2245063	.0531412	4.225	0.000	.1203282	.3286845
lnIRBX + IRBXcoth+IRBX12= 0.0	.1932629	.054206	3.565	0.000	.0869973	.2995284

11.3 Regression Tables, continued

11.3.2 Expansion Model, HCRIS Sample

Regression 1a: Dependent Variable is Year-to-Year Change in Resident FTE Claimed for IME
Payment Policy Variable is lagged real marginal IME per Resident:
Interactions by time period but not academic status

```
GEE population-averaged model                    Number of obs      =     10551
Group variable:                   provider       Number of groups   =      1229
Link:                             identity       Obs per group: min =         1
Family:                           Gaussian                      avg =       8.6
Correlation:                  exchangeable                      max =        11
                                                 Wald chi2(22)      =    347.45
Scale parameter:                  250.1617       Prob > chi2        =    0.0000

                        (standard errors adjusted for clustering on provider)
         |             Semi-robust
   dFTE3 |      Coef.   Std. Err.       z     P>|z|       [95% Conf. Interval]
---------+--------------------------------------------------------------------
 mIME3_1 |    .289674   .0963092     3.008   0.003        .1009114   .4784367
 IME33_5 |  -.2904815    .099036    -2.933   0.003       -.4845886  -.0963745
IME36_12 |  -.2708232   .0958493    -2.826   0.005       -.4586844   -.082962
  d_rout |   .6310461   .1079437     5.846   0.000        .4194803    .842612
  d_crit |   1.362352   .3170825     4.297   0.000        .7408818   1.983822
 lnf44_b2 |  .8401105   .4383667     1.916   0.055       -.0190725   1.699294
 lnFTE3_1 |  .1956728   .1272021     1.538   0.124       -.0536386   .4449843
 lnDSHind |  .6406259   .1858653     3.447   0.001        .2763365   1.004915
  public |  -.4644983   .4322245    -1.075   0.283       -1.311643   .3826461
 NIHcat1 |   .5979722   .9070247     0.659   0.510       -1.179763   2.375708
 NIHcat2 |   3.036259   1.428797     2.125   0.034        .2358676    5.83665
 NIHcat3 |   4.908079   2.608879     1.881   0.060       -.2052304   10.02139
    coth |   .6549524   .3187885     2.055   0.040        .0301384   1.279766
     ahc |   2.351443   1.133101     2.075   0.038         .130606    4.57228
 largurb |   .3229406   .2450189     1.318   0.187       -.1572875   .8031688
compcat2 |   .2738155   .2060256     1.329   0.184       -.1299872   .6776182
compcat3 |   .1739287   .2872126     0.606   0.545       -.3889976   .7368551
totmrgx1 |   2.034026    1.54926     1.313   0.189       -1.002468    5.07052
  MCAID2 |   .2984632    .232724     1.282   0.200       -.1576675   .7545938
      NY |   1.986846   .6717839     2.958   0.003        .6701735   3.303518
  PPS3_5 |   4.997201   2.160399     2.313   0.021        .7628958   9.231505
 PPS6_12 |   5.431486   2.023298     2.684   0.007        1.465895   9.397076
   _cons |  -10.53538   2.500538    -4.213   0.000       -15.43634   -5.63441
------------------------------------------------------------------------------
```

linear combinations on interacted variables:

dmaFTE3	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
mIME3_1 + IME33_5 = 0.0	-.0008075	.0144807	-0.056	0.956	-.0291892	.0275741
mIME3_1 + IME36_12 = 0.0	.0188508	.0075986	2.481	0.013	.0039579	.0337438

Appendix 3.2

Regression 1b: Dependent Variable is Year-to-Year Change in Resident FTE Claimed for IME Payment Policy Variable is lagged real marginal IME per Resident: Interactions by both time period and academic status

GEE population-averaged model		Number of obs	=	10551
Group variable:	provider	Number of groups	=	1229
Link:	identity	Obs per group: min	=	1
Family:	Gaussian	avg	=	8.6
Correlation:	exchangeable	max	=	11
		Wald chi2(24)	=	358.82
Scale parameter:	248.5675	Prob > chi2	=	0.0000

(standard errors adjusted for clustering on provider)

dFTE3	Coef.	Semi-robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
mIME3_l	.2578091	.0914471	2.819	0.005	.078576	.4370422
IME3coth	.0293875	.0194646	1.510	0.131	-.0087625	.0675374
IME3ahc	.1698733	.0371352	4.574	0.000	.0970897	.2426569
IME33_5	-.2777639	.0961546	-2.889	0.004	-.4662235	-.0893043
IME36_12	-.2530949	.0920292	-2.750	0.006	-.4334688	-.072721
d_rout	.6346699	.1082437	5.863	0.000	.4225162	.8468237
d_crit	1.378359	.3181154	4.333	0.000	.7548644	2.001854
lnf44_b2	1.119094	.4044373	2.767	0.006	.3264114	1.911776
lnFTE3_l	.1392326	.1266086	1.100	0.271	-.1089157	.3873809
lnDSHind	.6613759	.1912362	3.458	0.001	.2865598	1.036192
public	.0245005	.4217281	0.058	0.954	-.8020713	.8510723
NIHcat1	.8185991	.9272187	0.883	0.377	-.9987161	2.635914
NIHcat2	2.994131	1.474401	2.031	0.042	.1043576	5.883904
NIHcat3	4.268261	2.659209	1.605	0.108	-.9436924	9.480215
coth	-.6496196	.9791045	-0.663	0.507	-2.568629	1.26939
ahc	-3.530176	1.64453	-2.147	0.032	-6.753395	-.3069574
largurb	.2761091	.2492707	1.108	0.268	-.2124525	.7646708
compcat2	.4099953	.2161716	1.897	0.058	-.0136932	.8336838
compcat3	.3376601	.2935199	1.150	0.250	-.2376283	.9129486
totmrgxl	1.751578	1.606783	1.090	0.276	-1.397659	4.900815
MCAID2	.2431353	.232148	1.047	0.295	-.2118664	.698137
NY	1.874653	.6638099	2.824	0.005	.5736099	3.175697
PPS3_5	4.716637	2.119723	2.225	0.026	.562057	8.871217
PPS6_12	4.963361	1.958804	2.534	0.011	1.124175	8.802547
_cons	-11.07113	2.518693	-4.396	0.000	-16.00768	-6.134586

linear combinations on interacted variables:

dmaFTE3	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
PPS Year 2 only:						
mIME3_l+IME3coth = 0.0	.2871966	.0937232	3.064	0.002	.1035025	.4708907
mIME3_l+IME3ahc = 0.0	.4276824	.1086944	3.935	0.000	.2146454	.6407194
PPS Year 3-5 only:						
mIME3_l+IME33_5 =0.0	-.0199548	.0151339	-1.319	0.187	-.0496168	.0097072
mIME3_l+IME3coth+IME33_5=0.0	.0094327	.0240029	0.393	0.694	-.0376122	.0564776
mIME3_l+IME3ahc +IME33_5=0.0	.1499185	.037145	4.036	0.000	.0771157	.2227213
IME33_5+PPS3_5 =0.0	4.43887	2.026807	2.190	0.029	.4664053	8.411341
PPS Year 6-12 only:						
mIME3_l+IME36_12 =0.0	.0047142	.0069398	0.679	0.497	-.0088876	.018316
mIME3_l+IME3coth+IME36_12=0.	.0341017	.0199744	1.707	0.088	-.0050474	.0732508
mIME3_l+IME3ahc+IME36_12 =0.	.1745875	.0371922	4.694	0.000	.1016922	.2474828
IME36_12+PPS6_12 =0.0	4.710266	1.870382	2.518	0.012	1.044386	8.376147

test PPS3_5+IME33_5= PPS6_12+IME36_12:

IME33_5 - IME36_12 + PPS3_5 - PPS6_12 = 0.0

chi2(1) = 0.16

Prob > chi2 = 0.6901

Regression 2: Dependent Variable: Average Annual Change in Residents Claimed for IME, Over Period PPS 2-5

Payment Policy Variables: lagged real marginal IME per Resident, PPS 2:
"IME3min"= interacted effect, on Minor Teaching Hospitals only
"IME3coth"= interacted effect, on Major Non-Academic Hospitals only
"IME3ahc"= interacted effect, on Academic Health Centers only

Sample: All Teaching Hospital in PPS 2, appearing in all years, PPS 2-5

Source	SS	df	MS
Model	3030.93502	19	159.522896
Residual	16940.3773	721	23.495669
Total	19971.3124	740	26.9882599

Number of obs	=	741
F(19, 721)	=	6.79
Prob > F	=	0.0000
R-squared	=	0.1518
Adj R-squared	=	0.1294
Root MSE	=	4.8472

dFTE3A	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
IME3min	.0115396	.0320778	0.360	0.719	-.0514375	.0745166
IME3coth	.1348848	.0712558	1.893	0.059	-.0050089	.2747786
IME3ahc	-.0930677	.093919	-0.991	0.322	-.277455	.0913196
droutA	.1740665	.1191091	1.461	0.144	-.0597756	.4079086
dcritA	1.292088	.3845504	3.360	0.001	.5371157	2.04706
lnf44_b2	.1845314	.6553664	0.282	0.778	-1.102123	1.471186
lnFTE3_1	-.1453835	.2473822	-0.588	0.557	-.6310589	.3402919
lnDSHind	-.1088587	.3981612	-0.273	0.785	-.8905525	.672835
public	.6697022	.6007075	1.115	0.265	-.5096426	1.849047
NIHcat1	-2.746004	1.262971	-2.174	0.030	-5.225543	-.2664653
NIHcat2	1.589703	1.564221	1.016	0.310	-1.481268	4.660674
NIHcat3	-2.340148	2.224766	-1.052	0.293	-6.707941	2.027645
coth	-1.921975	1.474257	-1.304	0.193	-4.816325	.9723749
ahc	7.249574	1.925837	3.764	0.000	3.468657	11.03049
largurb	.4453109	.573118	0.777	0.437	-.6798685	1.57049
compcat2	.2000466	.5815944	0.344	0.731	-.9417741	1.341867
compcat3	.1695974	.7402022	0.229	0.819	-1.283612	1.622806
totmrgxl	-1.133268	1.312378	-0.864	0.388	-3.709807	1.443271
MCAID2	.6455436	.4272733	1.511	0.131	-.1933048	1.484392
NY	(dropped)					
_cons	-2.043904	3.571337	-0.572	0.567	-9.055365	4.967557

Appendix 3.2

Regression 3: **Dependent Variable: Average Annual Change in Residents Claimed for IME, Over Period PPS 6-12**

Payment Policy Variables: lagged real marginal IME per Resident, PPS 2:
"IME3min"= interacted effect, on Minor Teaching Hospitals only
"IME3coth"= interacted effect, on Major Non-Academic Hospitals only
"IME3ahc"= interacted effect, on Academic Health Centers only

Sample: All Teaching Hospital in PPS 6, appearing in all years, PPS 6-12

Source	SS	df	MS
Model	9096.33912	20	454.816956
Residual	15360.7156	808	19.0107866
Total	24457.0547	828	29.5375057

Number of obs =	829
F(20, 808) =	23.92
Prob > F =	0.0000
R-squared =	0.3719
Adj R-squared =	0.3564
Root MSE =	4.3601

dFTE3B	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
IME3min	-.0047397	.0106031	-0.447	0.655	-.0255526	.0160733
IME3coth	.0411038	.0152168	2.701	0.007	.0112347	.0709728
IME3ahc	.1632398	.0280776	5.814	0.000	.1081262	.2183534
droutB	.6348348	.1565158	4.056	0.000	.3276092	.9420604
dcritB	2.181946	.612512	3.562	0.000	.9796434	3.384248
lnf44_b6	1.82503	.5867271	3.111	0.002	.6733409	2.976719
lnFTE3_1	.3673957	.1971909	1.863	0.063	-.019671	.7544625
lnDSHind	.6186046	.3111033	1.988	0.047	.0079386	1.229271
public	-1.047641	.5422821	-1.932	0.054	-2.112089	.0168069
NIHcat1	1.171107	1.038152	1.128	0.260	-.8666869	3.2089
NIHcat2	4.099809	1.28014	3.203	0.001	1.587016	6.612601
NIHcat3	4.205437	1.372897	3.063	0.002	1.510572	6.900302
coth	-1.477925	1.026621	-1.440	0.150	-3.493084	.5372343
ahc	-3.71393	1.583277	-2.346	0.019	-6.821751	-.6061091
largurb	.1338591	.4740496	0.282	0.778	-.796655	1.064373
compcat2	.4092513	.4986332	0.821	0.412	-.569518	1.388021
compcat3	.5140416	.6189372	0.831	0.406	-.7008727	1.728956
totmrgx1	-.5324605	1.562166	-0.341	0.733	-3.598843	2.533922
MCAID2	-.1981034	.3864809	-0.513	0.608	-.9567284	.5605216
NY	2.22976	.5609702	3.975	0.000	1.128629	3.330891
_cons	-10.19045	3.229884	-3.155	0.002	-16.5304	-3.850493

11.3 Regression Tables, continued

11.3.3 Expansion Models, IRIS Sample

Regression 1a: Total FTEs, IRIS data
Using GEE on Year-to-Year Changes

```
GEE population-averaged model                   Number of obs      =      3770
Group variable:                   provider      Number of groups   =      1062
Link:                             identity      Obs per group: min =         1
Family:                           Gaussian                     avg =       3.5
Correlation:                  exchangeable                     max =         5
                                                Wald chi2(20)      =    100.76
Scale parameter:                  332.1018      Prob > chi2        =    0.0000
                           (standard errors adjusted for clustering on provider)
---------+--------------------------------------------------------------------
(allFTEs)|              Semi-robust
difdme_i |      Coef.   Std. Err.       z     P>|z|       [95% Conf. Interval]
---------+--------------------------------------------------------------------
 IME3min | -.0111717    .0093223     -1.198   0.231      -.0294432    .0070997
IME3coth |  .0146126    .0483386      0.302   0.762      -.0801292    .1093544
 IME3ahc | -.0296175    .0875777     -0.338   0.735      -.2012667    .1420317
  d_rout |   .497358    .2061374      2.413   0.016       .0933361    .9013798
  d_crit |   .656315    .8655957      0.758   0.448      -1.040221    2.352851
lnf44_b6 |  1.675171    .6426179      2.607   0.009       .4156634    2.934679
lnFTE3_1 |  .3848883    .2040144      1.887   0.059      -.0149727    .7847492
lnDSHind |  .6423503    .3986968      1.611   0.107      -.1390811    1.423782
  public |  .1380175    1.027146      0.134   0.893      -1.875151    2.151186
 NIHcat1 |  2.159533    1.911265      1.130   0.259      -1.586478    5.905545
 NIHcat2 |  2.746395    3.323195      0.826   0.409      -3.766947    9.259737
 NIHcat3 |  10.77303    4.674604      2.305   0.021       1.610976    19.93509
    coth | -1.680403    2.836778     -0.592   0.554      -7.240386     3.87958
     ahc |  1.722299    4.048886      0.425   0.671       -6.21337    9.657969
 largurb |   .682738    .5031261      1.357   0.175       -.303371    1.668847
compcat2 |  -.417785     .414944     -1.007   0.314       -1.23106    .3954902
compcat3 | -.3555764    .6244269     -0.569   0.569      -1.579431    .8682779
totmrgxl |  8.496363    4.561771      1.863   0.063      -.4445432    17.43727
  MCAID2 |  .3119239    .4853773      0.643   0.520      -.6393983    1.263246
      NY |  1.719952    .9201764      1.869   0.062      -.0835601    3.523465
   _cons | -9.171377     3.45241     -2.657   0.008      -15.93798   -2.404778
------------------------------------------------------------------------------
```

Regression 1b: Total FTEs, IRIS data
Using OLS on Average Annual Change in FTEs, Covariates at PPS 6

```
Regression with robust standard errors                 Number of obs =     678
                                                       F( 20,   657) =    3.71
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.1525
                                                       Root MSE      =  9.0833

------------------------------------------------------------------------------
          |               Robust
avgdme_i  |      Coef.   Std. Err.       t     P>|t|       [95% Conf. Interval]
---------+--------------------------------------------------------------------
  IME3min |   -.016982   .0127089     -1.336   0.182      -.0419369    .007973
 IME3coth |   .0415177   .0396437      1.047   0.295       -.036326   .1193613
  IME3ahc |  -.0034124   .1540164     -0.022   0.982       -.305836   .2990113
  droutIB |   .8220049   .3568313      2.304   0.022       .1213376   1.522672
  dcritIB |   3.508725   2.413845      1.454   0.147      -1.231055   8.248506
 lnf44_b6 |   .8755982   1.252954      0.699   0.485      -1.584679   3.335876
 lnFTE3_1 |   .6151438   .3155438      1.949   0.052      -.0044521    1.23474
 lnDSHind |   .4612618   .5235931      0.881   0.379      -.5668558   1.489379
   public |  -1.403997   1.796744     -0.781   0.435       -4.93205   2.124055
  NIHcat1 |  -.4626243   2.947298     -0.157   0.875      -6.249884   5.324636
  NIHcat2 |  -.0551096    5.09358     -0.011   0.991      -10.05677   9.946549
  NIHcat3 |    15.2816   7.717609      1.980   0.048       .1274436   30.43575
     coth |  -2.813014   2.356489     -1.194   0.233      -7.440171   1.814144
      ahc |   2.807732   6.898669      0.407   0.684      -10.73837   16.35383
  largurb |   .1291772    .843111      0.153   0.878       -1.52634   1.784694
 compcat2 |  -.6703792   .5449704     -1.230   0.219      -1.740473   .3997145
 compcat3 |  -.4412048   1.041394     -0.424   0.672      -2.486067   1.603657
 totmrgxl |  -1.267772   3.477856     -0.365   0.716      -8.096824    5.56128
   MCAID2 |  -.4018653   .9913679     -0.405   0.685      -2.348497   1.544766
       NY |   2.281618   1.250754      1.824   0.069      -.1743383   4.737575
    _cons |  -3.874577   6.957185     -0.557   0.578      -17.53557   9.786421
```

Appendix 3.3

Regresson 2a: 1st post-graduate year FTEs only
Using GEE on Year-to-Year Changes

```
GEE population-averaged model                     Number of obs      =      3605
Group variable:                    provider       Number of groups   =       992
Link:                              identity       Obs per group: min =         1
Family:                            Gaussian                      avg =       3.6
Correlation:                  exchangeable                       max =         5
                                                  Wald chi2(20)      =     19.05
Scale parameter:                   205.5945       Prob > chi2        =    0.5189
                        (standard errors adjusted for clustering on provider)
```

PGY1 only difpgy1	Coef.	Semi-robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
IME3min	-.0095657	.0081752	-1.170	0.242	-.0255887	.0064573
IME3coth	.0079899	.0266631	0.300	0.764	-.0442687	.0602486
IME3ahc	.0224579	.0504714	0.445	0.656	-.0764642	.1213799
d_rout	-.1102331	.1291738	-0.853	0.393	-.3634092	.1429429
d_crit	.7998365	.6839666	1.169	0.242	-.5407133	2.140386
lnf44_b6	.6675599	.6627708	1.007	0.314	-.631447	1.966567
lnFTE3_1	.1382156	.2110326	0.655	0.513	-.2754006	.5518318
lnDSHind	.3750314	.3189224	1.176	0.240	-.250045	1.000108
public	.1908188	.7675539	0.249	0.804	-1.313559	1.695197
NIHcat1	-.4607036	1.647334	-0.280	0.780	-3.689418	2.768011
NIHcat2	-2.752176	2.266898	-1.214	0.225	-7.195214	1.690861
NIHcat3	-2.506632	2.936385	-0.854	0.393	-8.26184	3.248577
coth	-2.04543	1.791292	-1.142	0.254	-5.556299	1.465438
ahc	-1.243924	2.71845	-0.458	0.647	-6.571988	4.084139
largurb	-.0646369	.4671359	-0.138	0.890	-.9802064	.8509325
compcat2	-.2911753	.4738691	-0.614	0.539	-1.219942	.6375911
compcat3	.3890213	.6317869	0.616	0.538	-.8492583	1.627301
totmrgxl	2.84648	2.645912	1.076	0.282	-2.339413	8.032373
MCAID2	-.5055049	.4250729	-1.189	0.234	-1.338632	.3276226
NY	-.2137126	.6498032	-0.329	0.742	-1.487303	1.059878
_cons	-2.734185	3.485218	-0.785	0.433	-9.565086	4.096717

Regresson 2b: 1st post-graduate year FTEs only
Using OLS on Average Annual Change in FTEs, Covariates at PPS 6

```
Regression with robust standard errors                 Number of obs =     663
                                                       F( 20,   642) =    0.64
                                                       Prob > F      =  0.8836
                                                       R-squared     =  0.0489
                                                       Root MSE      =  5.3528

------------------------------------------------------------------------------
         |               Robust
 avgpgy1 |      Coef.   Std. Err.       t     P>|t|       [95% Conf. Interval]
---------+--------------------------------------------------------------------
 IME3min |  -.0247354   .0133118     -1.858   0.064       -.0508754    .0014045
IME3coth |   .0160469   .0244652      0.656   0.512       -.0319945    .0640884
 IME3ahc |  -.0269124   .0761786     -0.353   0.724       -.1765017    .1226768
 droutIB |  -.1490876   .2026978     -0.736   0.462       -.5471183    .2489431
 dcritIB |   1.703295   1.784859      0.954   0.340       -1.801572    5.208162
 lnf44_b6 |   .8694858    .819305      1.061   0.289       -.7393556    2.478327
 lnFTE3_1 |   .1095611   .2667431      0.411   0.681       -.4142333    .6333555
 lnDSHind |   .0055081    .365405      0.015   0.988       -.7120252    .7230414
  public |   .5442617   .8936528      0.609   0.543       -1.210574    2.299097
 NIHcat1 |  -1.708355   1.564027     -1.092   0.275       -4.779581    1.362872
 NIHcat2 |  -1.362056   2.269584     -0.600   0.549       -5.818762    3.094649
 NIHcat3 |  -.9643229   3.128733     -0.308   0.758       -7.108109    5.179464
    coth |  -2.205704   1.620169     -1.361   0.174       -5.387174    .9757663
     ahc |   .9173989   3.446068      0.266   0.790       -5.849528    7.684326
 largurb |  -.4555115   .6026289     -0.756   0.450       -1.638873    .7278503
compcat2 |    .078532   .5790371      0.136   0.892       -1.058503    1.215567
compcat3 |   1.136962   .8944975      1.271   0.204       -.6195327    2.893456
totmrgxl |   .6774303   1.271174      0.533   0.594       -1.818731    3.173591
  MCAID2 |  -1.465854   .6576562     -2.229   0.026       -2.757271    -.174437
      NY |  -.3494464   .7146609     -0.489   0.625       -1.752802    1.053909
   _cons |  -3.521807   4.143725     -0.850   0.396        -11.6587    4.615084
```

Regression 3a: Initial Certification Specialties Only
Using GEE on Year-to-Year Changes

```
GEE population-averaged model                   Number of obs      =      3771
Group variable:                    provider     Number of groups   =      1062
Link:                              identity     Obs per group: min =         1
Family:                            Gaussian                    avg =       3.6
Correlation:                  exchangeable                     max =         5
                                                Wald chi2(20)      =     84.76
Scale parameter:                   282.8383     Prob > chi2        =    0.0000
                         (standard errors adjusted for clustering on provider)
------------------------------------------------------------------------------
init cert|             Semi-robust
 difgrp1 |      Coef.   Std. Err.       z     P>|z|       [95% Conf. Interval]
---------+--------------------------------------------------------------------
 IME3min |  -.0017713   .0100342     -0.177   0.860       -.021438    .0178954
IME3coth |   .0142874   .0407255      0.351   0.726      -.0655332     .094108
 IME3ahc |  -.0594299   .0792805     -0.750   0.453      -.2148168    .0959569
  d_rout |   .4604918   .1849613      2.490   0.013       .0979744    .8230093
  d_crit |    .468075   .7730399      0.605   0.545      -1.047055    1.983205
lnf44_b6 |   1.104492   .5875861      1.880   0.060      -.0471556    2.256139
lnFTE3_1 |   .3909837   .1942172      2.013   0.044       .0103249    .7716424
 lnDSHind |  .9619646   .4918583      1.956   0.050        -.00206    1.925989
  public |   .0580985    .933546      0.062   0.950      -1.771618    1.887815
 NIHcat1 |   1.958978   1.824906      1.073   0.283      -1.617772    5.535728
 NIHcat2 |   .9007988   3.175936      0.284   0.777      -5.323922     7.12552
 NIHcat3 |   9.980204   4.542067      2.197   0.028       1.077916    18.88249
    coth |  -1.261848   2.413903     -0.523   0.601      -5.993011    3.469316
     ahc |   2.650686   3.837015      0.691   0.490      -4.869726     10.1711
 largurb |    .499314   .5150802      0.969   0.332      -.5102248    1.508853
compcat2 |   -.411182   .4009947     -1.025   0.305      -1.197117    .3747532
compcat3 |  -.3238552   .6344951     -0.510   0.610      -1.567443    .9197323
totmrgx1 |   9.146083   4.472166      2.045   0.041       .3807986    17.91137
  MCAID2 |   .4591027   .4483877      1.024   0.306       -.419721    1.337926
      NY |   .8739313   1.055346      0.828   0.408      -1.194509    2.942372
   _cons |  -5.842519   3.198796     -1.826   0.068      -12.11204    .4270061
------------------------------------------------------------------------------
```

Regresson 3b: Initial Certification Specialties only
Using OLS on Average Annual Change in FTEs, Covariates at PPS 6

Regression with robust standard errors

Number of obs =	678
F(20, 657) =	2.94
Prob > F =	0.0000
R-squared =	0.1354
Root MSE =	7.99

avggrp1	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
IME3min	-.0139813	.0108824	-1.285	0.199	-.0353498	.0073872
IME3coth	.0290651	.0382344	0.760	0.447	-.0460113	.1041414
IME3ahc	-.1273446	.1611045	-0.790	0.430	-.4436864	.1889973
droutIB	.6990671	.3489917	2.003	0.046	.0137936	1.384341
dcritIB	3.164431	2.122478	1.491	0.136	-1.003228	7.33209
lnf44_b6	.5747845	1.07181	0.536	0.592	-1.529801	2.67937
lnFTE3_1	.5239675	.2899918	1.807	0.071	-.0454549	1.09339
lnDSHind	.6282897	.4560211	1.378	0.169	-.2671449	1.523724
public	-1.744706	1.554751	-1.122	0.262	-4.797585	1.308173
NIHcat1	-.2096878	2.66069	-0.079	0.937	-5.434168	5.014792
NIHcat2	-2.047214	4.499055	-0.455	0.649	-10.88147	6.787046
NIHcat3	13.47035	6.115526	2.203	0.028	1.462019	25.47868
coth	-2.109864	2.183551	-0.966	0.334	-6.397444	2.177716
ahc	6.097033	6.868577	0.888	0.375	-7.389976	19.58404
largurb	-.2060243	.7013956	-0.294	0.769	-1.583271	1.171223
compcat2	-.7195458	.5109005	-1.408	0.159	-1.72274	.2836489
compcat3	-.0762681	.8264104	-0.092	0.926	-1.698992	1.546456
totmrgx1	-.6771476	2.82202	-0.240	0.810	-6.218412	4.864117
MCAID2	-.0220851	.8215281	-0.027	0.979	-1.635222	1.591052
NY	1.76632	1.090144	1.620	0.106	-.3742664	3.906906
_cons	-2.01605	5.85331	-0.344	0.731	-13.5095	9.4774

Regression 4a: Non-Surgical Specialties Only
Using GEE on Year-to-Year Changes

GEE population-averaged model		Number of obs =	3771
Group variable:	provider	Number of groups =	1062
Link:	identity	Obs per group: min =	1
Family:	Gaussian	avg =	3.6
Correlation:	exchangeable	max =	5
		Wald chi2(20) =	118.18
Scale parameter:	252.4999	Prob > chi2 =	0.0000

(standard errors adjusted for clustering on provider)

non-Surg difgrp2	Coef.	Semi-robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
IME3min	-.0015722	.0096911	-0.162	0.871	-.0205663	.017422
IME3coth	-.0004378	.0385884	-0.011	0.991	-.0760697	.075194
IME3ahc	-.0046807	.0750102	-0.062	0.950	-.1516979	.1423366
d_rout	.4038963	.164698	2.452	0.014	.0810942	.7266984
d_crit	.7062929	.7556586	0.935	0.350	-.7747708	2.187356
lnf44_b6	1.328007	.5809473	2.286	0.022	.1893711	2.466643
lnFTE3_1	.4065007	.1770071	2.297	0.022	.0595732	.7534282
lnDSHind	.9181303	.4752553	1.932	0.053	-.013353	1.849614
public	.1484677	.8588409	0.173	0.863	-1.534829	1.831765
NIHcat1	1.844925	1.739099	1.061	0.289	-1.563647	5.253496
NIHcat2	.5026655	3.133198	0.160	0.873	-5.638291	6.643622
NIHcat3	12.9429	4.107595	3.151	0.002	4.89216	20.99364
coth	.0823339	2.314107	0.036	0.972	-4.453232	4.617899
ahc	.8050079	3.588037	0.224	0.822	-6.227415	7.83743
largurb	.7420709	.4342931	1.709	0.088	-.1091279	1.59327
compcat2	-.489755	.3526306	-1.389	0.165	-1.180898	.2013882
compcat3	-.6097157	.5320308	-1.146	0.252	-1.652477	.4330455
totmrgxl	6.858297	3.29926	2.079	0.038	.3918665	13.32473
MCAID2	.4002208	.4427747	0.904	0.366	-.4676018	1.268043
NY	1.010196	1.062468	0.951	0.342	-1.072204	3.092596
_cons	-7.16351	3.162569	-2.265	0.024	-13.36203	-.9649886

Regression 4b: Non-Surgical Specialties Only
Using OLS on Average Annual Change in FTEs, Covariates at PPS 6

```
Regression with robust standard errors                 Number of obs =     678
                                                       F( 20,   657) =    4.03
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.1741
                                                       Root MSE      =  7.9164

------------------------------------------------------------------------------
         |               Robust
 avggrp2 |      Coef.   Std. Err.       t     P>|t|       [95% Conf. Interval]
---------+--------------------------------------------------------------------
 IME3min |  -.0100146   .0111666     -0.897   0.370       -.031941    .0119119
IME3coth |   .0163433   .0349926      0.467   0.641      -.0523675    .0850542
 IME3ahc |   -.085759   .1558058     -0.550   0.582      -.3916963    .2201783
 droutIB |     .58703   .2698641      2.175   0.030       .0571299     1.11693
 dcritIB |   4.074238    1.94226      2.098   0.036        .260453    7.888023
 lnf44_b6 |   .4315114   1.095582      0.394   0.694      -1.719754    2.582776
 lnFTE3_1 |    .684933   .2823242      2.426   0.016       .1305665      1.2393
lnDSHind |   .4957683   .4766164      1.040   0.299      -.4401067    1.431643
  public |   -1.35335   1.544827     -0.876   0.381      -4.386744    1.680044
 NIHcat1 |  -.9089819   2.672516     -0.340   0.734      -6.156685    4.338721
 NIHcat2 |  -1.828021   4.487872     -0.407   0.684      -10.64032    6.984281
 NIHcat3 |   15.91089   6.804286      2.338   0.020       2.550126    29.27166
    coth |  -.9610572   2.086127     -0.461   0.645      -5.057336    3.135222
     ahc |   5.398388   6.613149      0.816   0.415      -7.587067    18.38384
 largurb |    .032548   .7161569      0.045   0.964      -1.373684     1.43878
compcat2 |    -.77042   .4843096     -1.591   0.112      -1.721401    .1805614
compcat3 |  -.5023921   .8760274     -0.573   0.567      -2.222543    1.217759
totmrgxl |  -1.350934   2.934561     -0.460   0.645      -7.113183    4.411314
  MCAID2 |  -.2231502   .8573772     -0.260   0.795       -1.90668     1.46038
      NY |   1.890137   1.149952      1.644   0.101      -.3678868    4.148162
   _cons |  -1.841432    6.12673     -0.301   0.764      -13.87177     10.1889
```

Regression 5a: Primary Care Specialties Only
Using GEE on Year-to-Year Changes

```
GEE population-averaged model                   Number of obs      =      3771
Group variable:                   provider      Number of groups   =      1062
Link:                             identity      Obs per group: min =         1
Family:                           Gaussian                     avg =       3.6
Correlation:                 exchangeable                      max =         5
                                                Wald chi2(20)      =     49.79
Scale parameter:                  101.2386      Prob > chi2        =    0.0002
                         (standard errors adjusted for clustering on provider)
```

Primary Care difgrp3	Coef.	Semi-robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
IME3min	-.0025297	.0061098	-0.414	0.679	-.0145046	.0094452
IME3coth	-.0030096	.0207063	-0.145	0.884	-.0435933	.0375741
IME3ahc	.040647	.0295069	1.378	0.168	-.0171853	.0984794
d_rout	.2377425	.0926731	2.565	0.010	.0561066	.4193783
d_crit	.1015233	.3996317	0.254	0.799	-.6817406	.8847871
lnf44_b6	.4027857	.3430907	1.174	0.240	-.2696597	1.075231
lnFTE3_1	.2344519	.124857	1.878	0.060	-.0102633	.4791671
lnDSHind	.5341881	.2747946	1.944	0.052	-.0043994	1.072776
public	-.3702247	.5296798	-0.699	0.485	-1.408378	.6679285
NIHcat1	.9463764	1.012558	0.935	0.350	-1.038201	2.930954
NIHcat2	.786322	1.571978	0.500	0.617	-2.294698	3.867342
NIHcat3	3.013863	2.589158	1.164	0.244	-2.060793	8.08852
coth	-.3418926	1.417095	-0.241	0.809	-3.119349	2.435564
ahc	-1.848138	1.703267	-1.085	0.278	-5.18648	1.490205
largurb	.3133654	.3847116	0.815	0.415	-.4406554	1.067386
compcat2	-.423487	.2653182	-1.596	0.110	-.9435011	.0965271
compcat3	-.4767086	.4565069	-1.044	0.296	-1.371446	.4180285
totmrgxl	4.696624	2.280832	2.059	0.039	.2262751	9.166973
MCAID2	.1146112	.3084698	0.372	0.710	-.4899784	.7192009
NY	.2924745	.6033647	0.485	0.628	-.8900986	1.475048
_cons	-1.458561	1.908395	-0.764	0.445	-5.198946	2.281824

Appendix 3.3

Regression 5a: Primary Care Specialties Only
Using OLS on Average Annual Change in FTEs, Covariates at PPS 6

```
Regression with robust standard errors                 Number of obs =     678
                                                       F( 20,   657) =    1.88
                                                       Prob > F      =  0.0112
                                                       R-squared     =  0.0694
                                                       Root MSE      =  4.4822
```

avggrp3	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
IME3min	-.0076876	.006514	-1.180	0.238	-.0204783	.0051031
IME3coth	.0035958	.0223259	0.161	0.872	-.0402429	.0474345
IME3ahc	.025346	.0614028	0.413	0.680	-.0952235	.1459154
droutIB	.2499992	.2118211	1.180	0.238	-.1659288	.6659272
dcritIB	1.72127	1.192429	1.443	0.149	-.6201607	4.062702
lnf44_b6	.2808834	.5824806	0.482	0.630	-.8628645	1.424631
lnFTE3_1	.1930815	.1679191	1.150	0.251	-.1366412	.5228043
lnDSHind	.6198571	.318695	1.945	0.052	-.0059265	1.245641
public	-.8366533	.8338121	-1.003	0.316	-2.473911	.8006046
NIHcat1	-.1574468	1.526823	-0.103	0.918	-3.155488	2.840595
NIHcat2	-1.287362	2.286479	-0.563	0.574	-5.77705	3.202326
NIHcat3	3.668809	3.225517	1.137	0.256	-2.664756	10.00237
coth	-.5350202	1.430692	-0.374	0.709	-3.344299	2.274259
ahc	-.371447	2.882423	-0.129	0.898	-6.031318	5.288424
largurb	-.1006924	.4559789	-0.221	0.825	-.9960441	.7946593
compcat2	-.5344296	.3148225	-1.698	0.090	-1.152609	.0837499
compcat3	-.2223876	.5256133	-0.423	0.672	-1.254472	.8096967
totmrgx1	-1.773394	1.622805	-1.093	0.275	-4.959903	1.413116
MCAID2	.0362544	.462225	0.078	0.938	-.8713619	.9438707
NY	.774822	.6771126	1.144	0.253	-.5547437	2.104388
_cons	.0078796	3.26726	0.002	0.998	-6.407652	6.423411

Regression 6a: Hospital-Based Specialties Only
Using GEE on Year-to-Year Changes

```
GEE population-averaged model                     Number of obs      =      3771
Group variable:                    provider       Number of groups   =      1062
Link:                              identity       Obs per group: min =         1
Family:                            Gaussian                      avg =       3.6
Correlation:                  exchangeable                       max =         5
                                                  Wald chi2(20)      =    105.76
Scale parameter:                   22.23094       Prob > chi2        =    0.0000
                        (standard errors adjusted for clustering on provider)
```

HospBased difgrp4	Coef.	Semi-robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
IME3min	-.0001262	.0032624	-0.039	0.969	-.0065204	.006268
IME3coth	-.011603	.0136779	-0.848	0.396	-.0384112	.0152052
IME3ahc	-.0141234	.023504	-0.601	0.548	-.0601904	.0319435
d_rout	.0669074	.0404923	1.652	0.098	-.012456	.1462707
d_crit	.1177552	.2556923	0.461	0.645	-.3833926	.6189029
lnf44_b6	.4587807	.1949256	2.354	0.019	.0767335	.8408278
lnFTE3_l	.1187479	.053401	2.224	0.026	.0140838	.223412
lnDSHind	.1533063	.1388214	1.104	0.269	-.1187787	.4253912
public	.3389536	.3310706	1.024	0.306	-.309933	.9878401
NIHcat1	.3959882	.7122418	0.556	0.578	-.9999802	1.791956
NIHcat2	-.7234172	1.133743	-0.638	0.523	-2.945513	1.498679
NIHcat3	3.964479	1.487358	2.665	0.008	1.049311	6.879647
coth	.8535617	.9498115	0.899	0.369	-1.008035	2.715158
ahc	1.794595	1.224029	1.466	0.143	-.6044563	4.193647
largurb	.2457756	.1744221	1.409	0.159	-.0960854	.5876365
compcat2	-.0572372	.1516313	-0.377	0.706	-.3544291	.2399547
compcat3	-.0668087	.2268937	-0.294	0.768	-.5115121	.3778947
totmrgxl	1.053888	.7636965	1.380	0.168	-.44293	2.550705
MCAID2	-.0977289	.1716385	-0.569	0.569	-.4341341	.2386763
NY	.1286671	.3152489	0.408	0.683	-.4892093	.7465436
_cons	-2.768694	1.074344	-2.577	0.010	-4.874371	-.663018

Regression 6b: Hospital-Based Specialties Only
Using OLS on Average Annual Change in FTEs, Covariates at PPS 6

Regression with robust standard errors

Number of obs =	678
F(20, 657) =	4.24
Prob > F =	0.0000
R-squared =	0.2412
Root MSE =	2.287

avggrp4	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
IME3min	-.0036118	.0034157	-1.057	0.291	-.0103188	.0030953
IME3coth	-.0056005	.0150723	-0.372	0.710	-.0351963	.0239953
IME3ahc	-.0603185	.0393418	-1.533	0.126	-.1375693	.0169322
droutIB	.1818029	.0874135	2.080	0.038	.0101595	.3534464
dcritIB	.4564143	.4289695	1.064	0.288	-.3859022	1.298731
lnf44_b6	.299125	.3040576	0.984	0.326	-.2979169	.8961668
lnFTE3_1	.2635241	.0771931	3.414	0.001	.1119492	.415099
lnDSHind	-.0399873	.1338274	-0.299	0.765	-.3027682	.2227937
public	-.039903	.4810041	-0.083	0.934	-.9843937	.9045876
NIHcat1	.0066243	.765229	0.009	0.993	-1.495965	1.509214
NIHcat2	-.8859618	1.331761	-0.665	0.506	-3.500983	1.729059
NIHcat3	5.356707	1.808967	2.961	0.003	1.804653	8.908762
coth	.2834174	.9216101	0.308	0.759	-1.526239	2.093074
ahc	3.237065	1.712321	1.890	0.059	-.125216	6.599346
largurb	.1999144	.2427091	0.824	0.410	-.2766646	.6764934
compcat2	-.2416775	.1501994	-1.609	0.108	-.5366062	.0532511
compcat3	-.2084326	.2764514	-0.754	0.451	-.7512673	.3344021
totmrgxl	.9515469	.8828171	1.078	0.281	-.7819362	2.68503
MCAID2	-.2530263	.2483282	-1.019	0.309	-.7406389	.2345863
NY	.2595758	.3342887	0.777	0.438	-.3968273	.915979
_cons	-2.024722	1.689031	-1.199	0.231	-5.341272	1.291827

Regression 7a: Foreign Medical Graduates Only
Using GEE on Year-to-Year Changes

GEE population-averaged model		Number of obs =	3761
Group variable:	provider	Number of groups =	1059
Link:	identity	Obs per group: min =	1
Family:	Gaussian	avg =	3.6
Correlation:	exchangeable	max =	5
		Wald chi2(20) =	164.57
Scale parameter:	60.76786	Prob > chi2 =	0.0000

(standard errors adjusted for clustering on provider)

FMGs difdmeFM	Coef.	Semi-robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
IME3min	.0031886	.007518	0.424	0.671	-.0115465	.0179237
IME3coth	-.0170609	.0207957	-0.820	0.412	-.0578198	.023698
IME3ahc	-.0014278	.0484687	-0.029	0.976	-.0964247	.0935691
d_rout	-.0490167	.0514416	-0.953	0.341	-.1498403	.0518069
d_crit	.0178628	.2212941	0.081	0.936	-.4158657	.4515913
lnf44_b6	.641519	.3655263	1.755	0.079	-.0748994	1.357937
lnFTE3_l	.4726789	.1065164	4.438	0.000	.2639105	.6814473
lnDSHind	.6969682	.428939	1.625	0.104	-.1437369	1.537673
public	.0078253	.4207134	0.019	0.985	-.8167578	.8324085
NIHcat1	2.98749	1.67334	1.785	0.074	-.2921973	6.267177
NIHcat2	1.877045	2.618154	0.717	0.473	-3.254444	7.008533
NIHcat3	3.285437	3.952182	0.831	0.406	-4.460697	11.03157
coth	2.536075	1.249678	2.029	0.042	.0867507	4.9854
ahc	-1.512298	2.677455	-0.565	0.572	-6.760014	3.735418
largurb	.0736096	.3438447	0.214	0.830	-.6003135	.7475328
compcat2	-.2059332	.1959208	-1.051	0.293	-.5899308	.1780645
compcat3	.1467599	.3835252	0.383	0.702	-.6049357	.8984554
totmrgxl	2.490496	1.900586	1.310	0.190	-1.234585	6.215576
MCAID2	.2738571	.2527343	1.084	0.279	-.2214931	.7692073
NY	1.503976	1.078289	1.395	0.163	-.6094317	3.617383
_cons	-4.113915	2.124107	-1.937	0.053	-8.277089	.0492578

Regression 7b: Foreign Medical Graduates Only
Using OLS on Average Annual Change in FTEs, Covariates at PPS 6

Regression with robust standard errors — Number of obs = 3761; F(21, 1058) = 8.02; Prob > F = 0.0000; R-squared = 0.0514; Root MSE = 7.7921

Number of clusters (provider) = 1059

difdmeFM	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
IME3min	.0012172	.0086859	0.140	0.889	-.0158264	.0182608
IME3coth	-.0214209	.0209559	-1.022	0.307	-.0625409	.019699
IME3ahc	-.0089623	.0487305	-0.184	0.854	-.1045817	.0866572
d_rout	-.0449399	.0524342	-0.857	0.392	-.1478268	.057947
d_crit	.0118059	.2225095	0.053	0.958	-.4248042	.448416
lnf44_b6	.6382933	.3792336	1.683	0.093	-.1058422	1.382429
lnFTE3_1	.5003293	.1049913	4.765	0.000	.2943145	.7063442
lnDSHind	.613535	.4705496	1.304	0.193	-.3097815	1.536851
public	-.0135131	.422721	-0.032	0.975	-.8429799	.8159538
NIHcat1	2.987696	1.679921	1.778	0.076	-.3086589	6.284051
NIHcat2	1.958275	2.642201	0.741	0.459	-3.226274	7.142823
NIHcat3	3.555112	3.9962	0.890	0.374	-4.286266	11.39649
coth	2.636298	1.251444	2.107	0.035	.1807048	5.091892
ahc	-1.403919	2.710659	-0.518	0.605	-6.722797	3.914959
largurb	.0489116	.350322	0.140	0.889	-.6384933	.7363165
compcat2	-.2251533	.1978188	-1.138	0.255	-.6133151	.1630085
compcat3	.157215	.3921176	0.401	0.689	-.6122016	.9266316
totmrgxl	2.282371	1.895216	1.204	0.229	-1.436439	6.001181
MCAID2	.2509261	.257121	0.976	0.329	-.253599	.7554511
NY	1.445851	1.080185	1.339	0.181	-.6736966	3.565399
p3	.52316	.2976633	1.758	0.079	-.0609174	1.107238
_cons	-4.442126	2.314463	-1.919	0.055	-8.983585	.0993325

Appendix 3.3

Regression 8: Testing for Sample Bias attributable to restricted time period Using HCRIS dependent variable, with indicators for IRIS period:

GEE population-averaged model		Number of obs	=	7008
Group variable:	provider	Number of groups	=	1197
Link:	identity	Obs per group: min	=	1
Family:	Gaussian	avg	=	5.9
Correlation:	exchangeable	max	=	7
		Wald chi2(22)	=	299.78
Scale parameter:	300.2655	Prob > chi2	=	0.0000

(standard errors adjusted for clustering on provider)

dFTE3	Coef.	Semi-robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
IME3min	-.0011965	.0094083	-0.127	0.899	-.0196365	.0172434
IME3coth	.0332759	.0300666	1.107	0.268	-.0256536	.0922054
IME3ahc	.1317905	.0466657	2.824	0.005	.0403273	.2232537
d_rout	.8537738	.1417707	6.022	0.000	.5759084	1.131639
d_crit	2.242163	.4333111	5.174	0.000	1.392888	3.091437
lnf44_b6	2.077349	.5027994	4.132	0.000	1.09188	3.062817
lnFTE3_1	.2603704	.154481	1.685	0.092	-.0424068	.5631477
lnDSHind	.7008394	.2752041	2.547	0.011	.1614492	1.24023
public	-.4946047	.5738134	-0.862	0.389	-1.619258	.6300489
NIHcat1	1.441545	1.370139	1.052	0.293	-1.243877	4.126967
NIHcat2	4.170915	1.953882	2.135	0.033	.3413777	8.000453
NIHcat3	8.125686	3.042305	2.671	0.008	2.162878	14.08849
coth	-1.065641	1.73079	-0.616	0.538	-4.457928	2.326646
ahc	-2.920845	2.298965	-1.271	0.204	-7.426734	1.585043
largurb	.0888904	.3584604	0.248	0.804	-.6136791	.7914599
compcat2	.1375554	.2629604	0.523	0.601	-.3778375	.6529483
compcat3	.6494767	.4063905	1.598	0.110	-.1470341	1.445988
totmrgxl	.9705023	2.314104	0.419	0.675	-3.565059	5.506063
MCAID2	-.0768209	.2920063	-0.263	0.792	-.6491427	.4955009
NY	2.315766	.7275434	3.183	0.001	.8898067	3.741724
PPS12	**-.1982544**	**2.2207**	**-0.089**	**0.929**	**-4.550746**	**4.154237**
IME3_12	**.0122747**	**.0332415**	**0.369**	**0.712**	**-.0528775**	**.0774269**
_cons	-11.56887	2.763831	-4.186	0.000	-16.98588	-6.151855

Regression 9: Testing for Sample Bias attributable to IRIS reporting hospitals Using HCRIS dependent variable, with indicators for IRIS hospitals

```
GEE population-averaged model                    Number of obs      =      5968
Group variable:                      provider    Number of groups   =      1157
Link:                                identity    Obs per group: min =         1
Family:                              Gaussian                   avg =       5.2
Correlation:                     exchangeable                   max =         6
                                                 Wald chi2(22)      =    248.81
Scale parameter:                     307.6796    Prob > chi2        =    0.0000

                       (standard errors adjusted for clustering on provider)
```

dFTE3	Coef.	Semi-robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
IME3min	.0321122	.020316	1.581	0.114	-.0077065	.0719309
IME3coth	.0779882	.0332157	2.348	0.019	.0128866	.1430898
IME3ahc	.1638128	.0795464	2.059	0.039	.0079047	.319721
d_rout	.7837291	.2007585	3.904	0.000	.3902497	1.177208
d_crit	1.986771	.5626763	3.531	0.000	.8839454	3.089596
lnf44_b6	2.636489	.6847632	3.850	0.000	1.294377	3.9786
lnFTE3_1	-.1162416	.1848498	-0.629	0.529	-.4785406	.2460575
lnDSHind	1.06349	.3170678	3.354	0.001	.4420487	1.684932
public	-.1948431	.7231226	-0.269	0.788	-1.612137	1.222451
NIHcat1	.8785088	1.516165	0.579	0.562	-2.09312	3.850137
NIHcat2	4.377779	2.458563	1.781	0.075	-.4409154	9.196474
NIHcat3	8.374772	3.683309	2.274	0.023	1.155619	15.59393
coth	-1.341657	1.860428	-0.721	0.471	-4.988028	2.304715
ahc	-.7102421	3.46715	-0.205	0.838	-7.505731	6.085247
largurb	.3091613	.4127426	0.749	0.454	-.4997993	1.118122
compcat2	.3688384	.3138712	1.175	0.240	-.2463379	.9840146
compcat3	.511677	.4370012	1.171	0.242	-.3448296	1.368184
totmrgxl	.1711651	2.50553	0.068	0.946	-4.739583	5.081914
MCAID2	-.0341159	.4028007	-0.085	0.933	-.8235907	.755359
NY	2.676936	.8603485	3.111	0.002	.9906838	4.363188
IRIS	**2.345658**	**1.396847**	**1.679**	**0.093**	**-.3921122**	**5.083428**
IME3IRIS	**-.0308742**	**.0243112**	**-1.270**	**0.204**	**-.0785234**	**.016775**
_cons	-15.9822	4.178492	-3.825	0.000	-24.1719	-7.79251

11.3 Regression Tables, continued

11.3.4 Conversion Models

Regression 1: Single Period, 12-year Probability Model
1(a): Using potential IME payments calculated from base year:

Logit Estimates — Number of obs = 3352; chi2(15) = 223.98; Prob > chi2 = 0.0000; Log Likelihood = -762.26202; Pseudo R2 = 0.1429

convrt01	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
mIMEstar	.005162	.0039339	1.312	0.189	-.0025483	.0128723
bed2	.5445936	.280497	1.942	0.052	-.0051705	1.094358
bed3	1.109479	.3011898	3.684	0.000	.5191575	1.6998
ORcat	.1924314	.1213888	1.585	0.113	-.0454862	.4303491
mdcat2	.4017976	.3211627	1.251	0.211	-.2276697	1.031265
mdcat3	.9211691	.3422428	2.692	0.007	.2503855	1.591953
DSHcat2	.2302343	.1629349	1.413	0.158	-.0891122	.5495808
DSHcat3	.6521654	.2062044	3.163	0.002	.2480122	1.056319
coth3	.5500988	.2137299	2.574	0.010	.1311958	.9690018
prop	-.1930969	.1786439	-1.081	0.280	-.5432326	.1570387
public	-.0141729	.1862198	-0.076	0.939	-.379157	.3508111
loc2	.0278463	.2788954	0.100	0.920	-.5187786	.5744711
loc3	.3831852	.3713994	1.032	0.302	-.3447442	1.111115
loc4	.2843467	.2647601	1.074	0.283	-.2345736	.8032671
loc5	.6987943	.320025	2.184	0.029	.0715567	1.326032
_cons	-5.163038	.4736574	-10.900	0.000	-6.09139	-4.234687

Exponentiated Results:

convrt01	Odds Ratio	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
mIMEstar	1.005175	.0039543	1.312	0.189	.9974549	1.012955
bed2	1.723908	.483551	1.942	0.052	.9948429	2.987263
bed3	3.032777	.9134413	3.684	0.000	1.680611	5.472851
ORcat	1.212193	.1471467	1.585	0.113	.9555328	1.537794
mdcat2	1.494509	.4799805	1.251	0.211	.7963873	2.804611
mdcat3	2.512226	.8597913	2.692	0.007	1.28452	4.913334
DSHcat2	1.258895	.2051179	1.413	0.158	.9147429	1.732527
DSHcat3	1.919693	.3958492	3.163	0.002	1.281476	2.875765
coth3	1.733424	.3704847	2.574	0.010	1.140191	2.635313
prop	.8244021	.1472744	-1.081	0.280	.5808675	1.170041
public	.985927	.1835991	-0.076	0.939	.6844382	1.420219
loc2	1.028238	.2867707	0.100	0.920	.5952472	1.776191
loc3	1.46695	.5448243	1.032	0.302	.7084015	3.037743
loc4	1.328894	.3518381	1.074	0.283	.790908	2.232824
loc5	2.011326	.6436747	2.184	0.029	1.074179	3.766069

Regression 1: Single Period, 12-year Probability Model
1(b): Using potential IME payments calculated from mid-point (PPS 6):

Logit Estimates — Number of obs = 3350; chi2(15) = 223.16; Prob > chi2 = 0.0000; Pseudo R2 = 0.1421

Log Likelihood = -762.84505

convrt01	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf. Interval]	
mIME6	.002425	.004324	0.561	0.575	-.0060499	.0108998
bed2	.5530235	.2808686	1.969	0.049	.0025311	1.103516
bed3	1.122922	.3008034	3.733	0.000	.5333584	1.712486
ORcat	.1884765	.1217866	1.548	0.122	-.0502209	.4271738
mdcat2	.4085535	.3209122	1.273	0.203	-.2204228	1.03753
mdcat3	.9548751	.3395893	2.812	0.005	.2892924	1.620458
DSHcat2	.2290633	.1627917	1.407	0.159	-.0900026	.5481292
DSHcat3	.6485897	.2074327	3.127	0.002	.2420289	1.05515
coth3	.5415233	.2149387	2.519	0.012	.1202513	.9627954
prop	-.2166631	.1765111	-1.227	0.220	-.5626186	.1292924
public	-.0287286	.1860555	-0.154	0.877	-.3933907	.3359335
loc2	.0266735	.2791469	0.096	0.924	-.5204443	.5737914
loc3	.3912373	.3737829	1.047	0.295	-.3413638	1.123838
loc4	.3041847	.2668477	1.140	0.254	-.2188271	.8271966
loc5	.7450813	.3223479	2.311	0.021	.113291	1.376872
_cons	-5.072578	.4655092	-10.897	0.000	-5.984959	-4.160196

Exponentiated Results:

convrt01	Odds Ratio	Robust Std. Err.	z	P>|z|	[95% Conf. Interval]	
mIME6	1.002428	.0043345	0.561	0.575	.9939684	1.010959
bed2	1.738501	.4882905	1.969	0.049	1.002534	3.014747
bed3	3.073824	.9246167	3.733	0.000	1.704648	5.542725
ORcat	1.207409	.1470462	1.548	0.122	.9510194	1.532919
mdcat2	1.50464	.4828572	1.273	0.203	.8021795	2.822237
mdcat3	2.598346	.8823704	2.812	0.005	1.335482	5.055404
DSHcat2	1.257422	.2046978	1.407	0.159	.9139288	1.730013
DSHcat3	1.912841	.3967859	3.127	0.002	1.273831	2.872407
coth3	1.718623	.3693985	2.519	0.012	1.12778	2.619007
prop	.8052012	.142127	-1.227	0.220	.5697152	1.138023
public	.9716801	.1807864	-0.154	0.877	.6747651	1.399246
loc2	1.027032	.2866929	0.096	0.924	.5942564	1.774984
loc3	1.478809	.5527537	1.047	0.295	.7108003	3.076641
loc4	1.355519	.3617172	1.140	0.254	.8034606	2.286899
loc5	2.106613	.6790621	2.311	0.021	1.119958	3.962486

Regression 2: Three-Period Model

Logit Estimates

Number of obs = 11411
chi2(17) = 243.15
Prob > chi2 = 0.0000
Pseudo R2 = 0.1186

Log Likelihood = -922.87536

(standard errors adjusted for clustering on provider)

convert	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
mIMEstar	-.0000517	.0036811	-0.014	0.989	-.0072665	.0071631
bed2	.38196	.2710696	1.409	0.159	-.1493267	.9132467
bed3	.7354664	.2872259	2.561	0.010	.1725141	1.298419
ORcat	.2999777	.0975506	3.075	0.002	.1087819	.4911734
mdcat2	.672433	.4449267	1.511	0.131	-.1996073	1.544473
mdcat3	1.274928	.4668996	2.731	0.006	.3598218	2.190034
DSHcat2	.0278185	.1735893	0.160	0.873	-.3124102	.3680473
DSHcat3	.5006125	.1961003	2.553	0.011	.116263	.884962
coth3	.3950309	.2099991	1.881	0.060	-.0165599	.8066216
prop	-.3091502	.1778791	-1.738	0.082	-.6577867	.0394864
public	-.2218035	.2326658	-0.953	0.340	-.6778201	.2342131
loc2	-.3756162	.3355404	-1.119	0.263	-1.033263	.2820309
loc3	-.1171615	.4813536	-0.243	0.808	-1.060597	.8262742
loc4	.3301224	.2773915	1.190	0.234	-.2135551	.8737998
loc5	.7021933	.3307606	2.123	0.034	.0539145	1.350472
g5	-.1966769	.193455	-1.017	0.309	-.5758417	.1824879
g9	.506505	.1767709	2.865	0.004	.1600404	.8529696
_cons	-6.871088	.5404455	-12.714	0.000	-7.930342	-5.811834

Exponentiated Results:

convert	Odds Ratio	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
mIMEstar	.9999483	.0036809	-0.014	0.989	.9927598	1.007189
bed2	1.465153	.3971586	1.409	0.159	.8612877	2.492401
bed3	2.086455	.5992838	2.561	0.010	1.188289	3.663499
ORcat	1.349829	.1316767	3.075	0.002	1.114919	1.634233
mdcat2	1.958998	.8716103	1.511	0.131	.8190523	4.685503
mdcat3	3.578444	1.670774	2.731	0.006	1.433074	8.93552
DSHcat2	1.028209	.1784861	0.160	0.873	.7316813	1.44491
DSHcat3	1.649731	.3235128	2.553	0.011	1.123291	2.422892
coth3	1.48443	.311729	1.881	0.060	.9835765	2.240327
prop	.7340705	.1305758	-1.738	0.082	.5179965	1.040276
public	.8010727	.1863822	-0.953	0.340	.5077226	1.263914
loc2	.6868659	.2304713	-1.119	0.263	.3558438	1.32582
loc3	.8894415	.4281359	-0.243	0.808	.3462489	2.28479
loc4	1.391138	.38589	1.190	0.234	.8077077	2.395998
loc5	2.018174	.6675326	2.123	0.034	1.055394	3.859247
g5	.821456	.1589147	-1.017	0.309	.5622315	1.2002
g9	1.659481	.293348	2.865	0.004	1.173558	2.346605

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